Stifling or Scaling? Acquisitions and their Effect on Start-up Innovation

Marius Berger[1], Sara Calligaris[1], Andrea Greppi[1], Dmitri Kirpichev[1]

Over the past two decades, incumbent firms have increasingly acquired innovative start-ups. Against a backdrop of rising industry concentration, declining business dynamism, and fewer disruptive innovations, this trend raises significant policy concerns. However, the studies analysing the effect of acquisitions on start-up innovation remain limited. This paper uses a unique firm-level cross-country dataset to examine the relationship between start-up acquisitions and their innovation performance across 60 countries. The findings indicate that acquisition targets are highly innovative before the deal, and acquirors are generally innovation-oriented firms. The acquired start-ups are also technologically closer and tend to share industries and countries with their acquirors, indicating potential for technological and product market synergies. However, start-up patenting tends to decline post-acquisition, with no corresponding increase in the acquirors' innovation activity. In addition, the paper provides suggestive evidence about the mechanisms driving this result, pointing to an anti-competitive strategy of the acquiror to suppress competitors and protect their markets.

[1] OECD Directorate for Science, Technology and Innovation

This document, as well as any data and map included herein, are without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

Restricted Use - À usage restreint

Disclaimer

This document, as well as any data and any map included herein, are without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

Acknowledgements

The report is a deliverable to the project “Building a Robust Innovative entrepreneurship ecosystem for a Digital and Green Economy” (BRIDGE) financed under Work Programme Horizon Europe – 2021-2022 Horizontal support expenditure for Horizon Europe and Euratom Programmes under grant no. LC-01965673.

The authors would like to thank Valentina Di Girolamo, Erik Canton and Julien Ravet (DG RTD) for their support throughout this project and for their insightful feedback on an earlier version of the report.

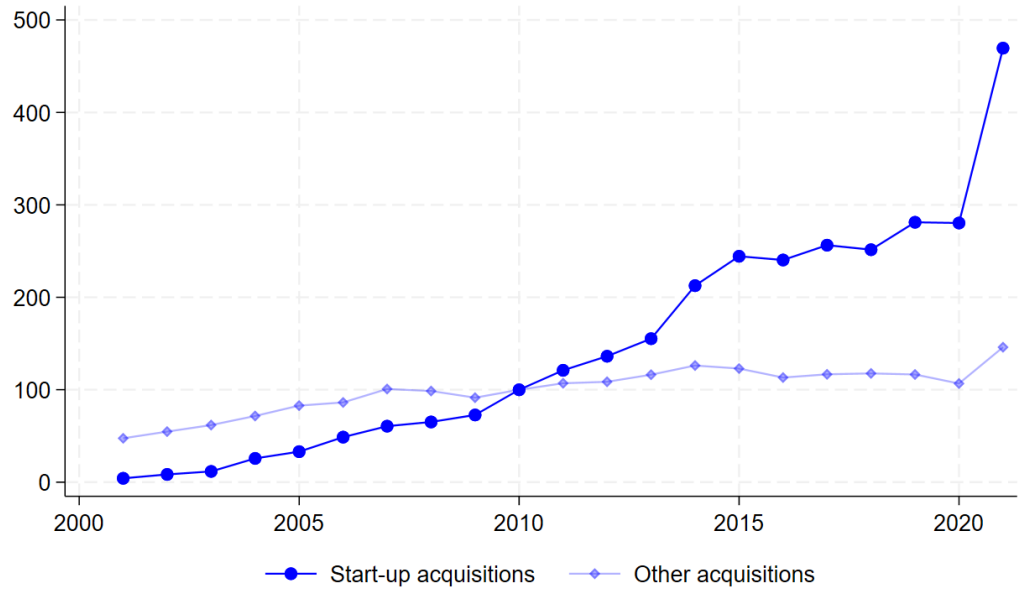
The authors also thank Antoine Dechezleprêtre, Hélène Dernis, Guy Lalanne for their important contributions to this project, Charles Parry for his excellent research assistance, and Shai Somek for technical assistance.



1 Introduction

Start-ups play a crucial role in driving technological advancement and economic development. Despite their small size, these companies account for a disproportionate amount of job creation (Haltiwanger, Jarmin and Miranda, 2013[1]), output growth (Haltiwanger, Jarmin and Miranda, 2017[2]), and innovation (Kortum and Lerner, 2000[3]). More importantly, start-ups are often the source of *radical* innovations (Schnitzer and Watzinger, 2022[4]) that lead to creative destruction, fostering competition, benefitting consumers, and enhancing productivity growth (Gans, H. and Stern, 2002[5]; Akcgit and Kerr, 2018[6]).

Figure 1.1. Incumbent companies have lifted their stakes in start-ups.



Note: The figure shows the change in the number of acquisitions of start-ups, of incumbent firms (i.e., not start-ups) relative to 2010. Start-ups are firms that applied for their first patent or raised their first VC financing between 2001 and 2021 and did so before reaching ten years of age. Incumbent firms are all firms not respecting these criteria.

Source: OECD calculations based on OECD/STI Start-ups Database, Thomson Reuters, and Orbis M&A data.

Innovation- and growth-oriented start-ups have attracted the interest of established companies in recent decades. Figure 1.1 shows that these incumbents have substantially increased their stakes in start-up companies through acquisitions. Acquisitions are transactions in which an incumbent buys a majority stake in a target company to gain control over it. Before the acquisition, two separate entities maximise their profits independently. However, after acquiring more than 50% of the shares of the start-up, most of the decision-making power falls upon the incumbent. Relative to 2010, these kinds of transactions in which the control of the start-up is passed to the incumbent have increased five-fold. These increases surpass substantially those of other incumbent firms (i.e., not start-ups) which have increased approximately 50%

Restricted Use - À usage restreint

since 2010. Several factors can account for such trends. For instance, firms might have increasing incentives to engage in these interactions to take advantage of economies of scale following the rise of intangible assets in the last decades (Atalay, Hortacsu and Syverson, 2014[7]). Likewise, financial and monetary motives like portfolio diversification and search-for-yield can also account for these patterns (Alexandridis, Antypas and Travlos, 2017[8]; Bellavitis, Fisch and Vismara, 2023[9]), particularly in a context where the cost of risk is low such as the one during the last decade. Despite several alternative explanations associated with the observed trends, this paper focuses on the role of *innovation motives* and the consequences of these interactions on subsequent innovation.

The increasing interest of these incumbents in start-up companies may reflect a more fundamental shift in the process of scientific discovery and corporate innovation (Arora, Belenzon and Patacconi, 2017[10]; Arora, Belenzon and Sheer, 2021[11]) in times when it is becoming increasingly challenging to create novelties (Bloom et al., 2020[12]). Acquiring stakes in young, innovation-driven companies may be a strategy of incumbents to gain access to radical innovations, thereby providing a way to deal with declining research productivity and reflecting a more efficient way of organising their research and innovation process. Innovation can be potentially boosted through the technological diffusion that might take place between companies (Bloom, Schankerman and Van Reenen, 2013[13]), the access to complementary assets that allow scaling up technologies (Rhodes-Kropf and Robinson, 2008[14]; Bena and Li, 2014[15]), or the relaxation of financial and other constraints that allow the acquired company to run its operations more smoothly (Didier et al., 2021[16]), among others.

At the same time, increasing stakes of incumbents in start-up companies coincide with some concerning trends over the past two decades, such as rising industry concentration (Bajgar et al., 2023[17]), declining business dynamism (Calligaris et al., 2024[18]; Calvino, Criscuolo and Verlhac, 2020[19]), and a declining share of disruptive innovations (Park, Leahey and Funk, 2023[20]). Some consider that these aggregate patterns can be partly explained by the increasing stakes of large incumbents in start-ups. Cunningham, Ederer, and Ma (2021[21]) show that some large incumbents acquire companies to discontinue their innovative projects, thereby preserving market power and maintaining their dominant status quo. Likewise, other authors argue that the prospect of being acquired may trigger start-up entry and innovation (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[22]), but may also be internalised by start-ups, who increasingly develop projects that are more likely to appeal to incumbents and lead to acquisitions, rather than pursuing promising projects that could potentially disrupt the market (Warg, 2022[23]).

This paper, thus, asks: if there are technological reasons behind these start-up acquisitions, what forces dominate? While the answer to this question contributes to the debate on anti-trust policy in an obvious manner, it also contributes to a lively debate on the best way to scale up start-ups and their innovation (European Commission, 2024[24]). The literature on entrepreneurship has shown important differences across start-ups that exit through IPOs or acquisitions (Giot and Schwienbacher, 2007[25]). Likewise, recent papers have shown the increasing relative importance of acquisitions as an exit strategy for start-ups during the recent decades (Ewens and Farre-Mensa, 2020[26]; Ederer and Pellegrino, 2023[27]). However, the ex-post consequences on innovation of said exit strategies are much less understood, even more so in the context of start-ups in a global environment. Understanding them is crucial to assess policies that modify the trade-off between remaining independent, going public, or selling out and what the implications for productivity growth and business dynamisms are of the different exit strategies. While existing literature has focused on the role of acquisitions more generally, no evidence specifically addresses start-ups in a cross-country context. The increased importance of start-ups in recent years calls for an updated and thorough perspective on this topic.

The present study provides a comprehensive overview of the incumbents' engagement in start-ups in recent years across a broad set of countries. It focuses on two key themes regarding start-up acquisitions: first, it portrays the start-ups and incumbents engaging in start-up acquisitions, focusing specifically on

Restricted Use - À usage restreint

their innovation activities. Second, it examines the effects that these acquisitions have on the subsequent innovation performance of both incumbents and start-ups.

The analysis combines information from various data sources to build a unique dataset that provides a comprehensive picture of the global start-up landscape over the past two decades. The foundation for this data set is the OECD/STI Start-ups Database, which harmonises information from Crunchbase and Dealroom, two commercial data providers with information on start-up companies and venture capital transactions. Combining the two allows for a much broader coverage of start-up companies across different geographies with respect to the existing literature. This paper considers start-ups as young firms oriented toward innovation and growth. Therefore, to match this definition of start-up, only those firms in the OECD/STI Start-ups Database that meet specific criteria are included in the analysis.[1] The start-up data are further augmented with information from Orbis M&A, a global database on mergers, acquisitions, and minority stake investments (M&A, henceforth), and PATSTAT, a widely used source of information on patents maintained by the European Patent Office (EPO). The large, cross-country sample gathered for the analysis represents a key contribution of the paper.

The paper conducts three exercises to characterise the companies engaging in acquisitions. First, it focuses on characterising the acquired start-ups, by comparing them to non-acquired start-ups within the same industries and countries. It finds that acquired start-ups are more likely to have prior innovations (measured through patent applications) than non-acquired start-ups. Having more innovations and of higher quality (as measured through their 5-year forward citations) further increases the likelihood of acquisition among companies that hold at least one patent over the sample period. This positive effect of patent ownership on acquisition likelihood is particularly strong for younger start-ups and for those acquired across industries or countries.

Second, when focusing on the characteristics of acquirors, the paper shows that acquisitions are related to incumbents' innovation performance. Comparing acquirors to other incumbents that actively engage with start-ups through means other than acquisitions (i.e., minority stake investments), it shows that acquirors are more innovation-oriented than the latter, as they are more likely to hold patents, hold more of them, and are of better quality. On the one hand, this may suggest that incumbents need some level of absorptive capacity (i.e., a base level of technology) to acquire start-ups and effectively benefit from the interactions with them. In this respect, the analysis also shows that incumbents are more likely to acquire start-ups in a phase when their own innovation is growing, and therefore the evidence does not suggest that incumbents incur in these transactions to overcome a period of technological downturns (Zhao, 2009[28]). On the other hand, it may also suggest that innovation leaders (i.e., incumbents with a higher patent stock) engage more in start-up acquisitions to suppress the most disruptive and innovative competitors. These channels are still to be explored.

Third, the paper examines how the joint characteristics of start-ups and incumbents are related to the likelihood of an acquisition, focusing on the role of market overlap and the technological closeness of the target-acquiror pair. To answer this question, random pairs of start-ups and incumbent acquirors are formed and compared to the actual pairs that can be observed. The findings show that having similar technologies (i.e., publishing patents in similar technological fields) is associated with a higher likelihood of engaging in an acquisition. Likewise, acquiror-target pairs that share an industry or geography are also more likely to be observed. Finally, the evidence indicates that technological proximity is more relevant when acquisitions occur across industries. These findings lend themselves to different interpretations.

[1] Specifically, as explained in section 3, this paper considers as innovative start-ups those companies that are less than 10 years old when the first relevant event (either the first VC financing round or a patent) takes place. These thresholds are in line with previous literature (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[24]; Ederer and Pellegrino, 2023[29]). Note that, as explained later, the results of the paper are robust to the choice of the thresholds to define the start-up sample.

Restricted Use - À usage restreint

First, incumbents may use acquisitions to expand into new industries while leveraging technological synergies with their existing businesses. Second, acquirors may seek to acquire start-ups within the same industry but with different technologies to shut them down, as they could threaten their incumbent position. This could happen for example if a start-up develops a technology that allows it to produce the same product as the incumbent firms in a more efficient way.

Next, the paper focuses on the effects of acquisitions on subsequent innovation performance. The main findings show that start-ups' innovation performance decreases substantially following an acquisition. Importantly, this decline in the rate of innovation is not compensated by an increase in the follow-on innovation by the acquirors. However, the citation flows of the acquired start-up do not change relative to non-acquired start-ups despite the reduction in new patents, suggesting that old technologies might diffuse more easily after the acquisition. These results continue to hold when restricting the group of comparison to those with an announced but eventually withdrawn acquisition for reasons exogenous to innovation (e.g., failure to comply with liquidity requirements of regulatory bodies).[2]

Overall, the results of the paper suggest that access to innovation is a primary motive to acquire majority stakes in start-ups. Namely, the evidence highlights the positive role of patented innovation and the importance of technological overlap in bringing together start-ups and incumbents. However, the innovative performance of start-ups worsens upon acquisition, and that of incumbents remains on average virtually unchanged. This decrease can be interpreted in different non-mutually exclusive ways. Focusing on acquisitions, different exercises are performed to provide *suggestive evidence* of potential channels that might be at play.

First, the reduction in patenting activity might not correspond to a true decrease in innovation. For instance, these interactions may allow start-ups to shift their focus away from developing technologies to commercialising them. Viewed in that way, these would allow to bring innovations to the market. This interpretation is consistent with the finding that, while the patenting activity of acquired start-ups reduces – when measured through the number of new patents –, the yearly rhythm of citations does not. Since the paper finds a decline in patented inventions *after* the acquisition, the unchanged flow of citations suggests that innovations developed *before* the acquisition receive more citations after the deal occurs and, thus, are possibly diffused more easily. Alternatively, acquirors might target those firms that have already undergone the development phase and are entering this commercialisation phase of inventions.[3] As a first step to provide some evidence for this hypothesis, the paper looks at targets' sales and trademarks after acquisition and shows that they both decline sharply, without a compensating increase on the acquiror's side.

A change in the patenting activity might also suggest a change in the intellectual property strategy of the start-up rather than a decline in innovation. To look at this alternative hypothesis, the paper looks at the patenting activity across start-ups acquired by incumbents with different patenting levels, aiming to capture companies with different patenting strategies. Once acquired, start-ups might follow the patenting tradition of the acquirors, who might decide not to patent all new inventions and pursue other ways to protect them. This exercise shows that the reduction in patenting activity holds even for start-ups acquired by firms whose IP strategy primarily relies on patenting. This suggests that the results are not driven by a change in the IP strategy of start-ups.

[2] This restricted sample helps to mitigate some identification concerns mainly related to the sample selection, providing more causal evidence.

[3] Note, however, that the long-run consequences on innovation and consumer welfare in this scenario are still ambiguous. For example, acquirors could increase market power by commercialising the start-up's ideas in the market, potentially leading to higher prices for consumers and lower innovation in the long run.

Restricted Use - À usage restreint

Second, the literature highlights that start-ups might not aim to disrupt the market in the long run. Instead, they often enter the market primarily to patent ideas that complement those of incumbents and, once they achieve a buyout, they lack further incentives to continue innovating (*innovation-for-buyout*) (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[22]; Warg, 2022[23]). According to this view, a lively acquisition market would be characterised by start-ups with more incremental and, thus, potentially more niche, less cited innovations. On the contrary, a market in which acquisitions occur less frequently is less prone to incentivise start-ups to innovate to be bought. To test this hypothesis, this paper compares the average citation-weighted yearly flow of patents of acquired start-ups across sectors and countries with different levels of acquisition activity. Contrary to innovation-for-buyout, the evidence shows that most acquisitions happen in sectors and countries in which start-ups present higher levels of citation-weighted patent flows.

Third, it may also be that incumbents acquire start-ups to subsequently shut down their innovation efforts to stifle competition (*killer acquisitions*) (Cunningham, Ederer and Ma, 2021[21]). An incumbent might find it profitable to shut down a start-up because new inventions depreciate the value of existing ones, and to avoid a strong competitor in the long run. This paper finds that the decline in patenting is stronger when the acquiror and the target start-up share an industry, a country, or when they share both, supporting the view that acquirors try to kill potential competitors.

Note that the analysis provides only *suggestive evidence* about the possible mechanisms at play, and further research would be necessary to establish a causal relationship. For instance, it cannot be excluded that neither the start-up nor the acquiror is actively looking to decrease the start-up's patenting activity, but this decrease occurs because of inefficiencies associated with the transition from two independent entities into one united corporation. Likewise, the aggregate findings also hide many layers of heterogeneity. For instance, incumbent firms involved in cross-country and cross-industry acquisitions in the EU have a positive impact on patenting activity after the acquisition.

This paper proceeds as follows. Section 2 discusses a review of the relevant literature, while section 3 describes the different data used in the analysis. Sections 4 and 5 provide evidence, respectively, on the characteristics of firms engaging in acquisitions, and on their consequences on innovation performance. Finally, section 20982 concludes and describes the next steps of the project.

Restricted Use - À usage restreint

2 Literature review

This paper builds on a broad body of literature that explores the factors driving interactions between firms through acquisitions, as well as their impact on innovation. The effect of acquisitions on start-up innovation has gathered the interest of different fields, namely the Industrial Organisation and Entrepreneurship literatures. While an increasing amount of papers analyse the impact of these acquisitions on productivity at the aggregate level (Cavenaile, Celik and Tian, 2021[29]; Fons-Rosen, Roldán-Blanco and Schmitz, 2022[22]; Weiss, 2023[30]), this review largely focuses on firm-level studies along the lines of the present study. First, it reviews the literature characterising firms that engage in acquisitions. It follows with the studies exploring the ex-post effects of acquisitions on innovation measures.

Innovative characteristics of firms engaging in acquisitions

Both theoretical and empirical contributions have explored the innovative characteristics of companies involved in an acquisition, in most cases without focusing specifically on start-ups.[4] The theoretical contributions predict a positive impact of innovation on the likelihood of being acquired. For example, Phillips and Zhdanov (2013[31]) show that small firms (such as the start-ups on which this paper focuses) may decide to innovate more when they can sell out to larger firms. Along the same lines, Fons-Rosen, Roldán-Blanco and Schmitz (2022[22]) have argued that the prospect of getting acquired may constitute an incentive for start-ups to innovate and enter the market. Larger firms, in turn, often find it more convenient to access innovation through acquisition rather than developing R&D internally.

An empirical portrait of the characteristics of acquired firms has already been developed in various settings. Consistently with the theoretical predictions above, most of the literature confirms that being an active developer of technologies (either through R&D or patents) increases the probability of being acquired (Hoberg and Phillips, 2010[32]; Phillips and Zhdanov, 2013[31]; Bena and Li, 2014[15]; Altomonte, El-Mallakh and Sonno, 2024[33]). These papers use data from publicly listed companies in COMPUSTAT and Orbis. In this way, studies focusing on start-ups' selection into acquisitions are limited. An exception is Breschi, Lassébie, and Menon (2018[34]), who study the selection of start-ups into acquisitions using a cross-country sample from Crunchbase. They show that receiving an acquisition offer and raising venture capital is more likely when the inventors are among the start-up founders. Another exception is Wang (2018[35]) who exploits Crunchbase to show that entrepreneurs increasingly innovate in the potential acquirors' technological fields if their markets are more concentrated. Along the same lines, Warg (2022[23]) exploits a policy shock that boosted VC markets in the US to show that catering decreases as options to remain independent become less costly.

The selection of incumbents into acquisitions has produced more mixed results in the literature. For instance, Zhao (2009[28]) and Bena and Li (2014[15]) focus on COMPUSTAT acquirors who perform isolated acquisitions (i.e. acquirors who do not acquire firms year after year). The former shows that these acquirors have similar levels of patent counts when compared to other publicly listed firms, while Bena and Li

[4] This study focuses only on the innovation motives for M&A, while there might be other important determinants behind these strategies, such as supply chain linkages, asset complementarities, and access to new markets.

Restricted Use - À usage restreint

(2014[15]) show that they have a higher level of patents.[5] A notable shortcoming of these studies is the restriction to isolated acquisitions, excluding companies that engage in acquisitions year after year, despite these companies accounting for a disproportionate share of M&A activity. An exception that includes said acquirors is Hsu et al. (2021[36]), who leverage cross-country firm-level information from firms in Worldscope to show that more innovative acquirors are more likely to pursue cross-border deals, especially if they are located in low-innovation countries. An important contribution of the present paper is to use appropriate econometric techniques to incorporate *serial acquirors* (i.e., those that engage in acquisitions year after year) into the analysis.

The impact of acquisitions on innovation

An extensive literature has also explored the impact of M&A activities on innovation performance. Theoretically, scholars have argued that these interactions can have ambiguous effects on innovation. On the positive side, some research suggests that innovations may be more valuable in the hands of incumbents, as they might have greater resources to scale them up (Cabral, 2018[37]; Letina, Schmutzler and Seibel, 2021[38]). Moreover, small firms may benefit from the additional resources gained through these interactions, as they help overcome financial and other constraints (Fumagalli, Motta and Tarantino, 2020[39]; García-Santana et al., 2024[40]). On the other hand, a prominent strand of literature highlights the potential for incumbents to suppress future competition through acquisitions (Cunningham, Ederer and Ma, 2021[21]). Once incumbents gain control of a target company, they may restrict the start-ups' innovation to prevent their ideas from threatening their dominant position. New ideas can depreciate the value of existing ones, reducing the new entity's incentives to innovate (Federico, Langus and Valletti, 2017[41]; Denicolo and Polo, 2021[42]; Cavenaile, Celik and Tian, 2021[29]). From the target's perspective, start-ups might also innovate with the goal of being acquired, and once they achieve that objective is achieved, they may shift to more incremental innovation or cease innovating altogether (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[22]; Weiss, 2023[30]).

This question has been also extensively investigated empirically, and in line with the ambiguous theoretical predictions, mixed results have emerged. Recent industry-specific studies have traditionally supported the *killer acquisition* hypothesis. Notably, Cunningham, Ederer, and Ma (2021[21]) analyse the pharmaceutical industry in the US and find that acquired drug projects are less likely to be developed when they overlap with the acquiror's product portfolio, especially when the acquiror's market power is large due to weak competition or distant patent expiration. Other examples of industry-specific studies include Haucap, Rasch, and Stiebale (2019[43]) and Gautier and Lamesch (2021[44]). The former, also analysing the pharmaceutical industry, identifies a causal negative effect on the innovation of the merged entities and their rivals, as measured through patent counts. The latter focuses on acquisitions by GAFAM firms and shows that the target companies' products are usually discontinued after the acquisition.

Other studies closely related to this analysis include Zhao (2009[28]), Bena and Li (2014[15]), and Sevilir and Tian (2010[45]), all of which address similar questions using COMPUSTAT data for the US. Zhao (2009[28]) compares the innovation activities of acquirors to those of acquirors who initiated acquisition negotiations but ultimately withdrew. She finds that successful acquirors tend to increase their innovation activity relative to acquirors with unsuccessful bids post-transaction. Sevilir and Tian (2010[45]) follow a similar approach, showing that firms more engaged in M&A tend to patent more after acquisitions.[6] Bena and Li (2014[15]) – building on the methodology introduced by Seru (2014[46]) – compare the joint innovation of targets and acquirors whose acquisitions were completed versus those withdrawn for reasons exogenous

[5] Their control group includes acquisition targets, other acquirors, and firms not participating in acquisitions.

[6] Unlike the strategies of Bena and Li (2014[15]) and Seru (2014[48]), Zhao (2009[30]) and Sevilir and Tian (2010[47]) do not dwell on whether the bids were withdrawn for reasons exogenous to innovation.

Restricted Use - À usage restreint

to innovation.[7] While they find no overall effect on innovation, they show that pairs experience improved technological performance post-acquisition when there is technological overlap between the target and the acquiror.

Another set of studies exploiting both information on publicly listed and privately held companies also gathered mixed evidence. Altomonte, El-Mallakh, and Sonno (2024[33]) study the effect of acquisitions by business groups in the cross-country Orbis database, showing that the patenting activity of target companies declines, on average, after the acquisitions. However, they also show heterogeneous effects: innovation increases when the technology of the target and the acquiror differs but decreases when they are similar. This result contrasts with the findings in Bena and Li (2014[15]), who find positive effects when technologies are similar. In a single-country study, Stiebale and Reize (2011[47]) exploit a representative panel of small and medium-sized German firms and causally show that cross-border acquisitions harm the target's innovation. Similarly, Stiebale (2016[48]), using Amadeus data for European publicly listed and privately held companies, shows that the post-acquisition output of the merged entity increases substantially in the context of cross-border acquisitions. However, acquisition targets experience a decline in innovation, which the author attributes to the relocation of innovation from the target to the acquiror's country. Lastly, Farre-Mensa, Liu, and Nickerson (2022[49]) exploit US patent data, focusing on patent acquisitions of first-time inventors (which they call start-ups). They causally show that inventors whose patents get acquired by another company decrease substantially their innovative output following this event.

With respect to this literature, the contributions of this paper are manyfold. First, and most important, it offers a comprehensive analysis of the relationship between acquisition and innovation focusing specifically on start-ups. Exploring both the ex-ante characteristics and the post-deal effects on both sides of the acquisition delivers a complete picture of the dynamics. The focus on start-ups is motivated by their importance in developing innovation and new technologies.[8]

Second, this paper leverages a richer cross-country dataset, addressing the gap in prior literature that largely centres on US companies. By incorporating data from both developed and emerging economies, the paper captures broader trends that may not apply to the US alone.

Lastly, unlike previous studies that typically limit analysis to single-time acquirors, this paper includes "serial acquirors" – firms that engage in multiple acquisitions over time. Thanks to newly developed econometric methods, this analysis provides insights into the behaviour and performance of firms that frequently acquire start-ups. Understanding the characteristics and performance of these firms is extremely relevant when looking at innovation, as often firms at the innovation frontier engage in more than one start-up acquisition.

[7] Namely, acquisitions withdrawn due to adverse macroeconomic conditions, opposition from regulatory bodies, or competing bids.

[8] The narrow focus of this paper on start-ups also alleviates concerns about capturing other mechanisms and motives for M&A engagement, especially the ones concerning gains from changes in market structure (e.g., price increases). This is because it is unlikely that start-ups are acquired for said purposes.

Restricted Use - À usage restreint

3 Data

This paper combines several data sources for its analysis, covering start-ups, their financing events, and innovation activities. This section presents the different data sources used in the analysis, detailing how these data have been cleaned and linked for joint use. It concludes by presenting some descriptive statistics on the final sample used in the subsequent analysis.

Dataset

Data on start-ups are obtained from the OECD/STI Start-ups Database. This database combines data from Crunchbase and Dealroom, considered by investors and analysts among the most comprehensive sources of information on start-up activity in the US and Europe, respectively.[9] Data are collected from various sources like public news, company filings, domain and trade registries, and investor portfolios, among others. Crunchbase was founded in 2005 and Dealroom in 2013, but they contain retrospective information with a sufficiently large coverage from the early 2000s. These datasets are combined, curated, cleaned, and harmonised within the Productivity, Innovation, and Entrepreneurship (PIE) Division of the Science, Technology, and Innovation (STI) Directorate at the OECD to create a unique and comprehensive dataset on the worldwide start-up ecosystem.

Information on start-up acquisitions and other financial interactions with incumbent companies is provided by Orbis M&A, part of the Orbis platform from Moody's Analytics. Previously known as Zephyr, this dataset compiles information on M&A deals from media, press releases, financial reports, and administrative filings. It captures both domestic and cross-border M&As, capturing deals involving target and acquiring firms across all industries. It offers global deal coverage from 2001 onwards, with European deals available from 1997. In this paper, acquisitions are defined as transactions between incumbent and start-up companies in which the incumbent ends up with more than a 50% stake in the start-up.[10] The analysis excludes acquisitions in which more than one acquiror is recorded.

To characterise the innovative portfolios of the companies in the data, this study resorts to PATSTAT Global – Autumn 2023 Edition. This dataset is a snapshot of the bibliographic and legal events database of the European Patent Office (EPO) as of Autumn 2023. It contains detailed data on patents filed,

[9] The databases also include information on other geographies. For instance, approximately one-fourth of the observations in the OECD/STI Start-ups database are in different regions than North America and Europe. These datasets also present a better coverage of early-stage deals than other sources used in previous literature, such as VentureXpert (Wang, 2018[37]).

[10] There are instances in which acquirors and start-up targets engage in several minority stake acquisitions which end up in the latter owning more than a 50% stake in the former, but they are not recorded as majority stake acquisitions. These deals are also considered as majority acquisitions. In these cases, the date of acquisition is assumed to be the date of the transaction through which the acquiror went from owning a minority stake (<50%stake) to a majority stake (>50%stake).

Restricted Use - À usage restreint

published, and cited at the European and US patent offices.[11] Further information on the details of patent data is provided below.

To provide suggestive evidence on the possible channels driving the decline in patenting activity found after an acquisition takes place, additional variables from Orbis vintage 2022 and the OECD/STI IP Database are used to complement the analysis. The first database allows tracking the evolution of the financial statement variables – and specifically firm-level sales and productivity (henceforth, TFP) – of privately and publicly held firms using information from unconsolidated balance sheet data.[12] The second database allows tracking of the filing of new trademarks following the acquisition (standardised within the intellectual property office and year) from the OECD/STI IP Database. This database covers all trademarks registered at the EIPO (European Intellectual Property Office), the JIPO (Japanese Intellectual Property Office), and the USPTO.

Finally, the different datasets have been merged relying on the links available at the OECD/STI MicroData Lab. The links across datasets rely on a string-matching procedure that takes information about the companies — such as their names, countries, addresses, websites, or any other information available — to generate measures of similarity between pairs of companies across datasets. Pairs with similarity measures above a certain threshold are then assigned a unique identifier across datasets.[13] At the end of this procedure, firms belonging to the OECD/STI Start-ups Database, Orbis M&A, and PATSTAT are uniquely linked across the three different databases.

Identifying innovative start-ups

The paper focuses on innovative start-ups engaging in M&A activity, where start-ups are regarded as young, innovation- and growth-oriented firms. To ensure the analysis captures the relevant start-ups, the OECD/STI Start-ups Database is further refined based on the following three criteria:

1. The firm appears in the OECD/STI Start-ups Database and has been linked to Orbis M&A;
2. it had the first venture capital financing round or filed for the first patent between 2001 and 2021;
3. it is less than 10 years old when the first relevant event (the first financing round or patent) takes place.

The reasoning behind the three criteria is as follows: The first criterion ensures that for all start-ups included in the sample, there is information on their M&A, allowing to know whether they have been acquired or

[11] It is a snapshot of the EPO's bibliographic database, meaning that any patent applied at the EPO or cited by a patent that was applied at the EPO will be in the database. That is, if a patent applied at EPO cites a patent applied in another application authority other than the USPTO or the EPO, it will appear in the dataset as well, even though this one was never applied for in the EPO or USPTO. Now, there will be no information on the citations to these patents.

[12] Productivity is defined as the residual of the difference between gross output and the product of the three input, capital, labour, and material, times the corresponding elasticity of production with respect to each input. To compute TFP, in addition to the balance sheet information, also these elasticities are required. In this specific setting, elasticities are directly obtained by Calligaris et al. (2024[19]). Using the same dataset, and a similar cross-country sample for overlapping years (and to a large extent countries), Calligaris et al. (2024[19]) estimate gross-output production functions in three inputs (capital, labour, and material) using the Ackerberg, Caves, and Garth (2015[75]) methodology. Production functions are 3-digit industry-specific and constant across years.

[13] A pair of companies will be assigned a unique identifier if their Levenshtein distance, Jaro-Winkler distance, cosine similarity, and token frequency measures are above 80%. In a few instances, the algorithm assigns several companies in one dataset to a unique company in another. In these cases, one of the matches is selected at random. Out of approximately 93 thousand start-ups in our final sample, only 2% are affected by this.

Restricted Use - À usage restreint

not.[14] In other words, the sample restricts to matched observations across datasets because one cannot assert if those companies that were not matched have undergone an acquisition or not, and it is only for Orbis M&A companies that we know with certainty whether it is the case. Also, the OECD/Start-ups Database misses some information that is leveraged extensively in the analysis like the companies' industries, which we obtain from the Orbis M&A information. The second criterion narrows the sample to innovation-driven start-ups, in line with existing literature, where innovative start-ups are those with early-stage financing or patents (or both) (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[22]; Ederer and Pellegrino, 2023[27]).[15] Finally, the last criterion ensures the dataset captures actual start-ups rather than established companies.[16] Overall, these additional constraints aim at refining the start-up sample to focus exclusively on innovation- and growth-oriented start-ups, avoiding other types of young or small enterprises and mature established companies.

The narrow and strict definition used to define start-ups plays a crucial role in the analysis, as it guarantees that all the start-ups in the sample are comparable and attenuates selection concerns. The specific thresholds used in criteria 2 and 3 are as close as possible to the existing literature, even if they remain somewhat arbitrary. For this reason, extensive robustness checks have been performed throughout the different exercises carried out in this paper to assess whether any of these arbitrary choices drive the results. All the evidence reported in the remainder of the paper remains qualitatively the same if these conditions are not imposed.

Identifying incumbents

For the analysis of start-ups' acquisitions, incumbents are retrieved from the sample of start-ups by identifying all companies involved in a minority or a majority stake deal as investors or acquirors, respectively. Thus, the sample of incumbent firms includes companies in the Orbis M&A database stated as acquirors or investors of the above-mentioned sample of start-ups. Therefore, incumbent firms show up in the data either because they have acquired a start-up or because they have engaged in other types of minority stake investments with companies in the start-up sample. Looking only at incumbents that engage in interactions with start-ups, and distinguishing between those that acquire and those that do not (i.e., another source of funding) allows to keep in the sample firms that are comparable, reducing the selection concerns in the analysis.

[14] Note that all start-up appearing in the Orbis M&A data must have had some interaction with investors. These investments could be either acquisitions or CVC investments, other VC minority investments, or could also be the result of IPOs or other later stage investments.

[15] While venture capital rounds could be also potentially identified in Orbis M&A, the OECD/STI Start-ups Database presents more details on the specific kind of financing used, allowing to identify better the ones associated with innovative start-ups. Also, it allows to better track the amount raised in each financing round, which is used as a proxy for technological input.

[16] By established companies, the understanding in this paper is companies who exited the 'start-up' status. In general, this covers companies that went through an IPO, got acquired, or just aged. Sometimes more established companies might appear in the data, either because they use an instrument that is traditionally associated with innovative start-ups or because of the incomplete information on patents published before the period of analysis. Therefore, this paper imposes the additional restriction that companies must be less than 10 years old at the time of the first relevant event (i.e. the date of the first filed patent or the date of the first VC round).

Restricted Use - À usage restreint

Final sample

The final sample considered in the analysis includes 93 855 start-ups across 60 countries, active in 204 3-digit NACE Rev. 2 industries within the manufacturing and market services sectors.[17] In addition, countries with less than 50 companies are dropped. Similar country and industry restrictions are applied on the incumbent side, resulting in a sample of 156 681 companies active in 217 3-digit NACE Rev. 2 industries and 74 countries. The time horizon included in the analysis considers all acquisitions of start-ups from 2001 to 2021. For more information on the sample composition by industries and countries, see Table A A.1 in Annex A.

The dataset presents a series of improvements over prior literature. First, the sample of acquired firms is larger than most of the papers mentioned above studying the relationship between start-up acquisitions and innovation. In particular, the sample covers 17 902 acquired start-ups.[18] Second, the global coverage of start-ups in this dataset is a major advancement, as most of the existing literature is heavily focused on the US.

Key innovation variables

To characterise a firm's innovative performance, the paper uses patent data. While patents are an imperfect proxy for innovation and capture only a portion of the overall innovation efforts developed by firms, they are a widely established measure to proxy for innovation (Basberg, 1987[50]). Several different measures of innovation are leveraged in the paper.

First, the number of inventions filed by each company is computed. This is measured by counting the annual number of DOCDB patent families each company files. A DOCDB family consists of patents filed in different patent offices that cover the same invention, and the filing date of the earliest patent in the family is used as the invention's date of inception. If multiple companies apply for the same DOCDB family, the earliest filing date is assigned to all co-applicants if they applied simultaneously. Otherwise, only the first applicant receives the earliest date, and subsequent applicants are assigned their respective application dates. The annual count of a company's applied inventions is then standardised according to the total number of inventions filed in each patent authority, WIPO technological class, and year.[19] This standardisation accounts for variations in patenting practices across technologies, countries, and time. To calculate the stock of inventions, standardised invention flows are aggregated at the company level, with an initial stock starting in 1973 (to account for pre-sample inventions) and depreciating annually at a rate of 15%. The technological-class-specific invention stocks are also recorded to assess the technological proximity between companies (discussed further below).

Second, a quality measure of patenting activity is computed by weighting the number of inventions filed by each company with the 5-year forward citations. Because each patent within the same DOCDB family often includes several publications, the average 5-year forward citations across patents in the same DOCDB family is used to compute the citations-weighted count of inventions at the family level. Then, this measure

[17] As a robustness, the results remain virtually unchanged when replicated by excluding start-ups from the financial sector and those targets acquired by financial companies.

[18] For comparison, the number of acquired start-ups analysed in the papers that explicitly address the effect of start-up or small firm acquisitions on innovation at the firm level mentioned in Section 2 ranges between six and sixteen thousand acquired companies. Note that this upper bound comes from Farre-Mensa, Liu, and Nickerson (2022[51]) who track patent acquisitions in the USPTO dataset rather than company acquisitions. Also, these studies are mostly focused on a single country. Most of the papers that use the information on publicly listed companies also fall in this range.

[19] See https://www.wipo.int/documents/2948119/3215563/wipo_ipc_technology.pdf for more details on the WIPO technological classification.

Restricted Use - À usage restreint

is again standardised and aggregated for each company similarly to the unweighted flows and stocks. This measure aims at better capturing the relevance of each filed invention and is traditionally interpreted as a sign of the quality of the patent (Squicciarini, Dernis and Criuscolo, 2013[51]). While the simple patent count measure includes information from patent offices all around the world, information on citations is restricted to those patents applied in the EPO and US Patent and Trademark Office (USPTO, henceforth).

Third, the yearly citations made to the documents published by each company are computed. While the two previous measures will only increase if the company publishes a new patent, this measure also captures citations to older inventions. This enables to distinguish between the rate at which companies create new ideas, reflected in the count measures, and the use of the new and the old ideas of the company, reflected in its citations. Similarly, they are standardised by all citations given to documents in a specific publication authority, WIPO technological class, and year. Similarly to citation-weighted patent counts, note that information on citations is only available for patents applied at the EPO or USPTO.

Finally, measures of patent proximity between pairs of firms are constructed to capture the technological overlap. In other words, this variable aims at capturing whether firms patent inventions in similar technological fields, as defined by the WIPO classification. Following Jaffe (1986[52]), each firm *i* is characterised by a 1x35 vector of patent stocks F_i across the 35 WIPO technological fields.[20] Then, the measure of technological proximity between firms *i* and *j* is given by the cosine similarity between their vectors of patent stocks as

$$Technological\ Proximity_{ij} = \frac{F_i F_j'}{\sqrt{(F_i F_i')(F_j F_j')}}$$

where the measure is bounded between 0 and 1, indicating that firms publish in orthogonal WIPO fields when it is equal to 0 and identical ones when it is equal to 1.

Another important variable used in the analysis is the amount of venture capital (VC) raised by start-ups. While the patent measures proxy for the innovative outcomes of the company, the amount of VC capital can be used as a proxy for the input of the innovation process – in a similar way to what is usually done with R&D expenditures. This variable is important to characterise acquisition targets, as they are likely building their patent stocks using R&D expenditures as input. These R&D expenditures are likely to be financed from their funding rounds, as revenues are usually non-existent in the early stages of the firm's life cycle (Dickinson, 2011[53]). Therefore, the VC stock will proxy these innovative inputs in this setting. The reasoning is that firms with higher financing needs correlate with high R&D-intensity firms (Didier et al., 2021[16]).

Descriptive statistics

This section presents descriptive statistics on the final sample assembled for the analysis. First, the section compares acquired and non-acquired start-ups. Then it compares acquired start-ups before and after acquisition. Finally, it delves into the differences between acquiring and non-acquiring incumbents.

The upper panel of Table 3.1 presents descriptive statistics for non-acquired start-ups, while the lower panel is for the acquired ones. First, the table shows that acquired startups are, on average, more innovative than the control group companies. The first and second lines in each panel show the distribution

[20] How to allocate patents across WIPO fields can be done in different manners. This paper proceeds as follows. Imagine there are only 2 aggregate technological fields (WIPO families) for simplicity. Each aggregate field is composed of many disaggregated technological classes (IPC families). If a patent contributes to 3 disaggregated families covered by one aggregate technological field and another 2 disaggregated families in the other field, then the aggregate technological family-specific patent stocks will be 3/5 for the first family and 2/5 for the second one.

Restricted Use - À usage restreint

of the number of patents filed by each firm over the sample period. In the first row, all firms in each of the two samples are used, while the second row focuses on companies that file a patent during their life cycle. Acquired firms are more likely to file a patent, as reflected by the difference in the mean value of the first line between the upper and lower panels. However, the patent portfolio is similar across patent-holding companies as shown in the second row. In the third and fourth lines, an equivalent exercise shows the distribution of patents filed by each firm, where each patent is weighted by their 5-year forward citations. As seen in the third line, acquired firms present patents that are substantially more cited. The fourth line shows that these differences across groups hold for patent-holding start-ups. The differences in patenting quantity and quality are smaller when comparing the second and fourth line of each panel to the first and the third line, suggesting that the main difference between acquired and non-acquired start-ups is on the extensive margin (having a patent or not), rather than on the intensive margin (weighted and unweighted number of patents among patent-holding companies). This can be also seen in the proportion of firms that drop from the sample when restricting it to only patent-holding companies, i.e., all those start-ups that are in the sample because have received VC but never applied for a patent. While the number of start-ups from the first to the second row decreases by more than two-thirds in the upper panel, it only decreases by approximately one-half in the lower panel.

Next, Table 3.1 focuses on the amount of VC raised by start-ups. While the average amount of venture capital is higher for non-acquired companies, acquired companies are similar when we restrict to those with a strictly positive amount. This can be explained by the acquisition event: acquired companies infrequently raise capital through venture capital rounds since they draw funds from the corporate parent and internal capital market. The median start-up company in the sample gets acquired when they are seven years old. If a company is acquired early on, it is less likely it will resort to VC financing. Nevertheless, those who have time to raise funds before the acquisition, on average obtain similar financing to control group start-ups, corroborating their innovative profile.

Table 3.2 performs a similar exercise but looks only at acquired start-ups and compares the pre- and post-acquisition period (excluding the acquisition year itself) in the upper and lower panels, respectively. As can be seen, most of the patenting takes place before the acquisition, and companies decrease it substantially after being acquired, both when looking at simple and citation-weighted patents.[21]

The descriptive evidence reported in these two tables offers preliminary insights into the main findings of the paper. In the next sections, econometric analysis is performed to provide more robust results of the suggestive evidence highlighted in this subsection, regarding both the differences between acquired and non-acquired start-ups and the effects of acquisitions on start-up innovation performance.

[21] Note that the number of firms included varies across the upper and lower panels. This is so mainly due to firms acquired in the last year of data (2021) for which patents are not observed in the post-acquisition period.

Restricted Use - À usage restreint

Table 3.1. Descriptive statistics: acquired versus non-acquired start-ups.

Panel A. Never acquired					
	N	Mean	P25	P50	P75
Patents	75 953	2.1	0.0	0.0	1.0
Patents (only patenting start-ups)	22 444	7.0	1.0	2.0	6.0
Citations-weighted patents	74 060	58.4	0.0	0.0	0.0
Citations-weighted patents (only patenting start-ups)	22 444	197.5	0.0	7.0	42.0
Venture capital	75 953	16.8	0.0	0.6	5.6
Venture capital (only with VC)	49 348	25.9	0.7	2.9	13.0
Panel B. Acquired					
	N	Mean	P25	P50	P75
Patents	17 902	3.5	0.0	0.0	2.0
Patents (only patenting start-ups)	8 126	7.7	1.0	2.0	6.0
Citations-weighted patents	17 902	101.9	0.0	0.0	8.0
Citations-weighted patents (only patenting start-ups)	8 126	224.6	1.0	12.0	68.0
Venture capital	17 902	11.7	0.0	0.0	5.0
Venture capital (only with VC)	8 446	24.9	1.3	5.8	21.0

Note: This table presents descriptive statistics on non-acquired and acquired startups in the upper and lower panel, respectively. It shows different moments of the distribution of a selected number of innovation measures that include the mean, the first, the second, and the third quartiles, as well as the number of observations in each panel. The innovation measures include the number of patents, the citation-weighted patents, and the venture capital, all aggregated over the sample period for each company.
Source: OECD calculations based on Orbis M&A, OECD/STI Start-ups Database, and PATSTAT.

Table 3.2. Descriptive statistics: acquired start-ups before and after acquisition.

Panel A. Before acquisition					
	N	Mean	P25	P50	P75
Patents	17 623	2.4	0.0	0.0	1.0
Patents (only patenting start-ups)	8 013	5.3	1.0	2.0	5.0
Citations-weighted patents	17 623	93.5	0.0	0.0	6.0
Citations-weighted patents (only patenting start-ups)	8 013	205.5	0.0	9.0	58.0
Panel B. After acquisition					
	N	Mean	P25	P50	P75
Patents	15 182	1.1	0.0	0.0	0.0
Patents (only patenting start-ups)	7 038	2.3	0.0	0.0	1.0
Citations-weighted patents	15 182	8.5	0.0	0.0	0.0
Citations-weighted patents (only patenting start-ups)	7 038	18.3	0.0	0.0	0.0

Note: This table presents descriptive statistics on acquired startups before and after the acquisition in the upper and lower panel, respectively. It shows different moments of the distribution of a selected number of innovation measures that include the mean, the first, the second, and the third quartiles, as well as the number of observations in each panel. The innovation measures include the number of patents, the citation-weighted patents, and the venture capital, all aggregated over the period before and after the acquisition for each company (excluding the year of the event).
Source: OECD calculations based on Orbis M&A, OECD/STI Start-ups Database, and PATSTAT.

Restricted Use - À usage restreint

Finally, Table 3.3 focuses on the incumbent side. It presents descriptive statistics similar to Table 3.1 but for incumbent companies, distinguishing between those that acquire innovative start-ups and those that do not. Acquirors are substantially more innovative than incumbent companies that do not acquire start-ups across all patent measures considered. In all cases, the density of each patent measure for acquirors is shifted to the right with respect to the distribution presented by incumbents who chose to engage in interactions with start-ups through minority investments. The last row of each panel shows that acquirors acquire more than one start-up in our sample period, and not-acquiring incumbents also engage with several start-ups through minority investments. The last row of the bottom panel shows that most of the acquirors (more than 75% of them) are involved in only one acquisition. Given that the number of acquisitions is 17 902 and more than 75% of the 11 120 acquirors buy only one start-up, it follows that there are very few companies undertaking many acquisitions, the so-called “serial acquirors”.

Table 3.3. Descriptive statistics: acquiring versus non-acquiring incumbents.

Panel A. Never acquire					
	N	Mean	P25	P50	P75
Patents	145 561	4.2	0.0	0.0	0.0
Patents (only patenting start-ups)	13 772	44.0	1.0	3.0	11.0
Citation-weighted patents	145 561	38.1	0.0	0.0	0.0
Citation-weighted patents (only patenting start-ups)	13 772	394.9	0.0	4.0	40.0
Number of minority stakes	145 561	3.4	1.0	1.0	2.0
Panel B. Acquire					
	N	Mean	P25	P50	P75
Patents	11 120	18.3	0.0	0.0	1.0
Patents (only patenting start-ups)	3 492	59.7	1.0	4.0	15.0
Citation-weighted patents	11 120	392.7	0.0	0.0	0.0
Citation-weighted patents (only patenting start-ups)	3 492	1 250.0	1.0	19.0	186.0
Number of acquisitions	11 120	1.3	1.0	1.0	1.0

Note: This table presents descriptive statistics on non-acquiring and acquiring incumbents in the upper and lower panel, respectively. It shows different moments of the distribution of a selected number of innovation measures that include the mean, the first, the second, and the third quartiles, as well as the number of observations in each panel. The innovation measures include the number of patents and the citation-weighted patents, all aggregated over the sample period for each company. Similarly, it reports the distribution moments of the number of minority stakes in start-ups for non-acquiring companies and the number of acquisitions for acquiring ones.
Source: OECD calculations based on Orbis M&A, OECD/STI Start-ups Database, and PATSTAT.

Restricted Use - À usage restreint

4 What kind of firms engage in acquisitions?

This section characterises the companies in the dataset at the moment of acquisition, to understand whether target and acquiror firms have some key characteristics that distinguish them from other companies.

Methodology

The analysis below explores how the probability of acquisition depends on target or acquiror characteristics, and how the probability of a pair being formed depends on the joint characteristics of the acquiror-target pair. In other words, the paper answers the questions: (i) who the acquisition targets are, (ii) who the acquirors of start-ups are, and (iii) how pairs of targets and acquirors are formed.

As mentioned in the previous section, the sample of start-ups is composed of firms that receive the first VC investment or apply for the first patent between 2001 and 2021 and are less than 10 years old at said moment. The sample of acquired start-ups (treated targets) includes all the start-ups that were acquired between 2001 and 2021. These constitute approximately 20% of the companies in the final sample. The rest of the start-ups (i.e., non-acquired start-ups in the sample) represents the so-called control group. The analysis will compare the treated targets to the start-ups in the control group to understand if acquired start-ups have systematically different characteristics than start-ups in the control group.

As for the incumbent side, the sample comprises firms that according to Orbis M&A invested in the sample of start-ups. The analysis will compare incumbents acquiring majority ownership in a start-up (i.e., treated incumbents or, equivalently, acquirors) with other incumbent companies who actively choose other means of interaction with start-ups (i.e., invested in the final sample of start-up firms through minority stakes). The latter represents the control group when looking at incumbents.

Two different specifications are used to answer the first two questions. The first specification uses the cross-sectional variation in the data (i.e., it compares the levels of innovation across firms) to analyse how the innovation activity affects the probability of being acquired (acquiring). Specifically, the following regression is considered:

$$1\{Acquisition\}_{it} = \alpha_{sct} + \beta_1 * Innovation\ characteristics_{it-1} + \varepsilon_{it}, \qquad \text{Equation 1}$$

where the dependent variable is a dummy that takes the value 1 if an acquisition takes place for a target (acquiror) *i* at year *t,* and 0 otherwise; α_{sct} is a set of 3-digit NACE Rev. 2 industry (*s*)-country (*c*)-year fixed effects; and $Innovation\ charactertistics_{it-1}$ captures different measures of innovation for company *i* at time *t-1*, discussed later on. This specification exploits cross-sectional variation by comparing the levels of the variables of interest between acquired and non-acquired start-ups within the same country-industry-year. It allows understanding whether higher values of the explanatory variables - their innovation characteristics - are associated with a higher probability of being acquired (acquiring). The configuration of fixed effects allows controlling for all unobservable characteristics that are common to all start-ups

Restricted Use - À usage restreint

(acquirors) within the same country-industry-year. When looking at start-ups, the specification includes the age of the start-up as a control variable.

As the second specification, the following panel regression is performed:

$$1\{Acquisition\}_{it} = \alpha_i + \alpha_{sct} + \beta_1 * Innovation\ characteristics_{it-1} + \varepsilon_{it}, \qquad \text{Equation 2}$$

which follows firm *i* over time, and employs firm fixed effects, α_i, in addition to industry-country-year fixed effects α_{sct}. The regression looks at whether variation in the variables of interest within each target (acquiror) is associated with a change in the probability of being acquired (acquiring). Firm fixed effects allow to control for any time-invariant firm-specific unobservable variable.

Equation 1 exploits a repeated cross-section to identify the parameters of interest. Acquired start-ups (acquirors) are considered in the sample only in the year of acquisition, while the control group firms are considered multiple times. To have a meaningful control group and make sure that acquired start-ups are compared to similar start-ups, non-acquired start-ups are considered in the control group only up to 10 years before and after the first venture capital investment or 6 years before and after the first patent (depending on the relevant event).[22] This choice is made also to mitigate potential concerns about attrition of the start-up sample. In other words, this ensures that comparisons are not made against companies who exited the market, as the data is not well-suited to analyse exit dynamics, or more established companies as they grow older during the sample period.[23] Instead, Equation 2 uses a panel setting: each treated firm is followed throughout its lifetime from its birth onward while applying the same thresholds to the duration of control group companies in the sample. While the first specification examines whether treated start-ups (acquirors) have higher *levels* of innovation, the second specification investigates whether these firms show *increasing* levels of innovation leading up to the acquisition.

To answer the question on pair formation, the paper relies on a specification that allows to understand the pair characteristics that make deals more likely. Specifically, fictitious pairs are randomly formed (i.e., deals that could have occurred, but never did) to serve as a comparison against pairs that actually engaged in deals. By calculating various pair-wise explanatory variables for all transactions, the analysis compares these variables across both actual deals and their fictitious counterparts. This comparison provides insights into the characteristics that make certain pairs more likely to engage in deals.

The set of fictitious deals is built by matching each acquired target to three potential acquirors from the control group of incumbent firms, and each actual acquiror to three start-ups from the control group, i.e., start-ups that were not acquired. These matches are formed in two ways. First, the analysis randomly matches targets and acquirors. Second, the analysis matches acquirors to targets that have similar VC stocks and age as the acquired start-ups. Then, the following linear probability specification is considered:

$$\begin{aligned} 1\{Pair\ is\ formed\}_{ijt} & \qquad \text{Equation 3} \\ &= \alpha_{d(i,j)} + \beta_1 * Technological\ Proximity_{ijt-1} \\ &+ \beta_2 * Cross - Industry_{ij} + \beta_3 * Cross - country_{ij} + \varepsilon_{ijt}, \end{aligned}$$

where $1\{Pair\ is\ formed\}_{ijt}$ is a dummy variable that takes the value 1 if a deal takes place between target *i* and incumbent *j* at time *t*, and 0 otherwise, and $\alpha_{d(i,j)}$ is a menu-of-deals fixed effect. By construction,

[22] The results of the analysis remain qualitatively the same if this choice is not imposed and non-acquired start-ups are used as a control group throughout the timeframe considered. The results are available upon request. The thresholds are based on previous literature (Barrot, 2016[74]; Fons-Rosen, Roldán-Blanco and Schmitz, 2022[24]).

[23] Using the available data, start-ups in the sample exit the market on average when they are 9 years old and have their first IPO when they are 12 years old. Thus, the restriction is consistent with exit dynamics from the start-up status.

Restricted Use - À usage restreint

each menu-of-deals fixed effect is composed of seven deals: the actual one and six fictitious ones. Simply put, the specification is informative about which deal is more likely to happen out of each set of seven deals (1 actual deal + 6 fictitious ones). As such, this specification helps to understand the interplay between industries, countries, and technological overlap of each pair of target-acquiror.

$Technological\ Proximity_{ijt-1}$ is the primary focus of this specification. It is a measure of technological proximity à la Jaffe (1986[52]), which measures the overlap across technological classes of the patent portfolios of companies *i* and *j*. As explained in the previous section, this variable captures whether the innovation portfolios developed by two firms are similar, allowing to understand whether acquisitions mainly take place between firms with similar technologies or whether acquisitions mainly involve pairs that develop innovations far from each other. Since it is only possible to build this measure for patenting firms, this analysis is restricted to pairs in which both sides have patents. $Cross - Industry_{ij}$ is an indicator that takes value 1 if *i* and *j* are not in the same 3-digit industries, and $Cross - Country_{ij}$ is an indicator that takes value 1 if *i* and *j* are not in the same country. These variables will inform whether pairs are more likely to happen within the same country and industry, or whether acquisitions are used also to expand into new markets.

Since this identification strategy relies heavily on the fictitious matches for each target and acquiror, the analysis draws the set of deals 100 times without replacement and reports the results of the 100 Monte Carlo simulations to corroborate its robustness to the selection of the fictitious pairs. For each simulation, different random pairs are formed.

Acquisition of targets

Table 4.1 reports the results of Equation 1 (column 1-3) and Equation 2 (column 4-6) when looking at the acquisition of targets. The explanatory variables of interest are three alternative patent-related measures of innovation, as well as the amount of VC received over the last three years before the acquisition.

The first three columns in Table 4.1 show the results that leverage variation across firms in the independent variables within the same industries, countries, and years. The row labelled “mean dependent variable” reports the average probability of being acquired in the sample used in each column; this variable is used as a reference point for interpreting the magnitude of the results.[24] Likewise, the row labelled “premium” showcases the ratio between the coefficient of interest and the mean dependent variable. The first column shows that having (at least) a patent increases the probability of being acquired: for start-ups that did not secure any VC funding, having a patent before the acquisition increases the probability of being acquired by 0.92 p.p., which is approximately 37% of the average dependent variable.[25] Also, the amount of VC funds raised in the last three years before the acquisition is positively associated with the acquisition event. The positive association between VC funds and the probability of acquisition can be interpreted in different ways. On the one hand, firms that raised more VC funds can be more attractive to the acquiror since other investors showed interest in their potential. On the other hand, prior literature shows that there exists a correlation between R&D-intensive firms and higher financing needs (Didier et al., 2021[16]). Therefore, firms that raise more funds for their activity can potentially be more R&D-intensive as well.

[24] Note that this probability is different from the underlying probability of being acquired in the full sample, which is approximately 20% (17 thousand get acquired out of 93 thousand total start-ups). In this case, the probability ranges between 2% and 3% because the sample used to compute it is a repeated cross-section, and never acquired firms are repeated multiple times.

[25] It is computed as the ratio between the premium for patent holders, 0.0094, and the unconditional average probability of being acquired: 0.02.

Restricted Use - À usage restreint

Table 4.1. A description of acquired start-ups – which characteristics make a start-up more likely to be acquired?

	Cross-section			Within-firm		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Has a patent}_{t-1}$	0.0085***			0.0112***		
	(0.0006)			(0.0008)		
$\log(1+\text{Patent stock}_{t-1})$		0.0408***			0.0510***	
		(0.0113)			(0.0136)	
$\log(1+\text{Citations}-\text{weighted patent stock}_{t-1})$			0.0163***			0.0197***
			(0.0044)			(0.0059)
$\log(1+\text{VC stock}_{t-1})$	0.0006***	0.0005***	0.0005***	0.0012***	0.0010***	0.0010***
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Only patent holding start-ups	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	555 607	196 371	196 371	713 241	270 029	270 029
R-squared	0.0591	0.0791	0.0791	0.1482	0.1580	0.1580
Mean dep. variable	2.4	2.6	2.6	1.9	1.9	1.9
Premium	35.0	0.9	1.4	57.8	1.4	2.3

Note: The table shows the results of Equation 1 using cross-firm variation (first three columns) and Equation 2 using within-firm variation (last three columns). The first columns in each of the different specifications show the effect of a dummy variable that takes the value 1 if start-up i had a patent at time t-1 on the probability of being acquired (extensive margin). The next two columns in each set of three reflect the effect of the patent stock and citation-weighted patent stock among firms that ever held a patent during the sample period (intensive margin). The average dependent variable reports the unconditional probability of being acquired in the relevant sample in percentages. The premium shows the change in the probability of being acquired from having a patent in the first and third columns, and from increasing the stock from 0 to the average patent stock in the rest over the average dependent variable. All regressions control for the firm's age and industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.

Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A.

The next two columns restrict the sample to those companies that hold a patent at some point during the sample period and look at variation across firms.[26] In other words, these columns exploit the intensive margin of innovation (how many patents and of what quality) rather than the extensive margin of innovation (do firms have a patent or not). As can be seen, the positive coefficients indicate that the unweighted and citation-weighted number of patents is higher among acquired companies, even when considering only companies holding patents. This exercise using only patenting start-ups confirms the result of the previous column providing evidence that the results were not driven by the choice of selecting the sample based on having a patent. However, the results present large differences in the magnitude of the premium across extensive and intensive margins. Among the latter, the premium is the ratio between the effect of a change from a patent stock of 0 to a standardised patent stock equivalent to the average of this measure across companies in the considered sample. A simple back-of-the-envelope calculation using column 2 shows that a start-up that increases its patent stock from 0 to 2 patents (which is the average stock of patents in the sample of patent-holding start-ups) will increase its probability of being acquired by 0.9% of the average

[26] The specification considers log(1+Patent stock) to include in the sample all start-ups with a patent stock of zero, which otherwise would be removed. Note that this specification restricts the sample to those companies that hold a patent at some point during the sample period, and therefore some observations might have zero patents in some years until they apply for the first patent.

Restricted Use - À usage restreint

dependent variable.[27] This might suggest that the first patenting event is more relevant for the prospect of acquisition than the following. Alternatively, it might suggest that acquisitions are concentrated on the start-ups that were selected into the sample because they had a patenting event. Table A B.1 in the Appendix shows that while the difference in the premia between extensive and intensive margin decreases when selecting only VC-funded companies, there is still a large difference in magnitudes, suggesting that first-time patenting has a sizable effect, and that sample selection does not affect substantially this result.

This set of results is similar to the results reported by Bena and Li (2014[15]). Using a sample with patenting and non-patenting firms, they show that target companies have more patents and R&D expenditures than firms in the control group within their industries. Also, these differences are smaller when they are restricted to only patent-holding companies (specifically, they find non-statistically significant differences, while this paper finds that they decrease substantially).

The last three columns in Table 4.1 present the equivalent exercise exploiting within-firm variation. While the previous columns analyse how differences in levels of the explanatory variables affect the probability of being acquired, the next three columns assess the impact of changes over time in these variables for each firm. The magnitude, signs, and statistical significance of the coefficients remain very similar to the first specification, corroborating the results found. First, firms that transition from not having a patent to having one are substantially more likely to be acquired. Second, firms whose patent stock (weighted and not) increases before the acquisition are more likely to be acquired in the next period. An increasing amount of VC funds raised by the start-up also increases the likelihood of acquisition.

The combination of these results indicates that acquired start-ups not only have patents more frequently and in higher quantities but also that an increase in their patenting and R&D activities is associated with an increased probability of being acquired. These findings also align with the findings in Altomonte, El-Mallakh, and Sonno (2024[33]) who exploit a similar specification on a sample of privately and publicly held firms using the Orbis database.

Table 4.2 provides a better understanding of start-up targets by investigating possible heterogeneities across different dimensions. All these exercises are estimated relying on the cross-sectional framework of Equation 1. The first column allows the effect of having a patent to vary across age categories. Relative to start-ups below 3 years old (the omitted category in the table), the interaction term “Has a patent x Age” shows that the increase in the probability of being acquired stemming from having a patent is more important for start-ups 3–5 years old and even more for start-ups 6-10 years old, before becoming slightly negative for start-ups above 10 years old. Therefore, there is an inverted U-relationship between having a patent and the age profile of the company. This suggests that patents are more relevant for companies at early stages of the life cycle than later. For start-ups without VC funding and between 3 and 10 years old, having a patent can increase the likelihood of being acquired by approximately 50% with respect to the

[27] The increase in the probability of having a patent for a patent-holding company with no VC funds is given by the coefficient of the patent outcome of interest in column 2. To obtain the 0.9% premium, the following steps are done. The average log of ones plus the standardised patent stock is 0.0055. Multiplying 0.0055 by 0.0408 (the coefficient on the log of one plus the standardised stock of patents) gives 0.0002. The average probability of being acquired among patent-holding companies is 0.026 which yields 0.0002/0.026 = 0.009. Remember that this paper uses patent counts that are standardised across several dimensions (application authorities, WIPO fields, and time), and therefore the correspondence between a unit increase in the independent variable and the increase in the actual number of patents is not straightforward. To provide a more direct sense of the magnitude of the results, the same regression is performed using the unstandardised patent stock (simple patent count of each firm). In this case, a start-up that increases its stock from 0 to 1 patent will experience an increase equivalent to 19.7% of the average of the dependent variable.

Restricted Use - À usage restreint

average probability of being acquired. [28] For start-ups older than 10 years, instead, the premium of having a patent is statistically the lower than for start-ups younger than 3 years.

Table 4.2. Heterogeneity across acquired start-ups

		Age	Across industries	Within industries	Across countries	Within countries
		(1)	(2)	(3)	(4)	(5)
$\text{Has a patent}_{t-1}$		0.0040**	0.0078***	0.0016***	0.0043***	0.0051***
		(0.0017)	(0.0005)	(0.0004)	(0.0003)	(0.0005)
$\text{Age x Has a patent}_{t-1}$						
	3-5	0.0073***				
		(0.0019)				
	6-10	0.0078***				
		(0.0018)				
	+10	-0.0040*				
		(0.0022)				
$log(1 + VC\ stock_{t-1})$		0.0006***	0.0003***	0.0003***	0.0002***	0.0005***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations		540 637	535 417	530 615	529 858	536 179
R-squared		0.0609	0.0630	0.0374	0.0622	0.0554
Mean dep. variable		2.5	1.7	0.9	0.7	1.8
Premium		16.2	46.7	18.1	57.5	28.7

Note: The table shows the results of the linear probability model (Equation 1) using cross-sectional variation for different specifications. The first column allows the effect of having a patent to vary across age categories. The second and third columns only include acquisitions that happen across and within 3-digit NACE Rev. 2 industries, respectively. The fourth and fifth columns only include acquisitions that happen across or within countries, respectively. The control group never changes. The mean dependent variable reports the unconditional probability of being acquired in the relevant sample as a percentage. The premium represents the ratio between the coefficient of having a patent and the mean dependent variable as a percentage. All regressions control for the firm's age and industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on OECD/STI Start-ups Database, Orbis M&A, and PATSTAT data.

The next two columns explore if the characteristics of acquired start-ups are different depending on whether the acquisition was across or within the same 3-digit NACE industry. Specifically, the treated start-ups in the second column only include those that have been acquired by a company active in a different industry, while the third column only includes start-ups acquired by a company active in the same industry. In both columns, the full control group is included. The result shows that having a patent increases the average probability of being acquired by more than 45% of the average dependent variable when acquisitions happen across industries (for firms that did not raise any VC funds). Meanwhile, the premium of having a patent when acquisitions happen within the industry is down to 16% of the average probability of being acquired. Similarly, the fourth and fifth columns show the same pattern when acquisitions happen across or within countries. While having a patent increases the likelihood of acquisition by more than half the value of the baseline average probability (third column) when acquisitions happen across countries,

[28] As explained above, to obtain these numbers one needs to add up the premium on having a patent, given by the coefficient on "Has a patent" and its interaction with the age group category, and compare it against the average probability of acquisition in the sample, reported in the table. Therefore, the premium is (0.0040+0.0073)/0.025 and (0.0040+0.0078)/0.025 for companies between 3-5 years old and 6-10 years old, respectively. The coefficients of the age group are not reported in the table and are available upon request.

Restricted Use - À usage restreint

this premium is down to one-fourth of the average probability when we focus on acquisitions that happen within countries.[29]

Overall, the evidence reported in this subsection shows that innovation capabilities are an important factor affecting the likelihood of start-up acquisitions. In line with the existing literature, the findings show that acquirors are systematically more likely to target firms with patents, suggesting that start-up acquisitions are potentially related to innovation motives. Having a patent could signal to investors start-up quality and commitment to innovation. Alternatively, patents and the use of technological inputs may also provide insightful information into the company's activity in a market with informational asymmetries, helping investors to choose which start-ups are worth engaging. This is especially the case since some start-ups are acquired even before they commercialise their businesses. This idea is reinforced by the different heterogeneity exercises carried out, which point to the stronger importance of patents when the transactions entail higher uncertainty: when start-ups are younger, and hence less likely to have already started commercialising their products, or when the market of activity of the start-ups is further away from the acquiror's (either across countries or industries), the signals stemming from patents are more relevant.

[29] Note that, as already mentioned in the previous section, extensive robustness checks have been performed to assess whether the results depend in any possible way on the choices made while selecting the relevant sample. As written above, all the results of this analysis remain qualitatively unchanged when different choices on the sample selection are made.

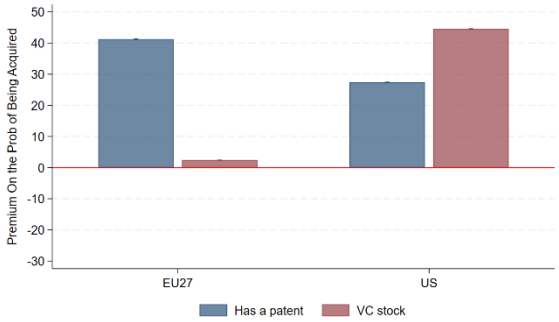
Restricted Use - À usage restreint

Box 4.1. Start-up targets across regions and sectors.

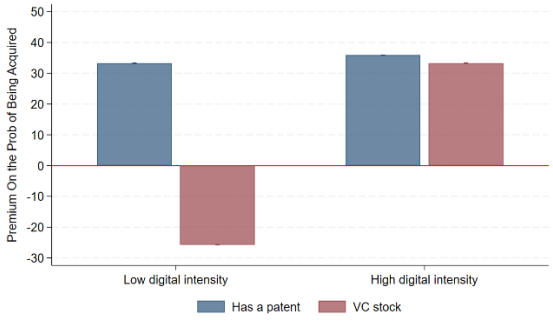
The EU-US productivity wedge during the last decades has sparked a lively policy debate and it has triggered numerous papers in academic literature aimed at understanding its causes and consequences (European Commission, 2024[54]). Many have linked it to the importance of the intangible and digital economy (De Ridder, 2024[55]). For this reason, this box provides an additional portrayal of acquired innovative start-ups exploring their differences across the US and the EU, and low and high digitally intensive sectors. Using their industry of activity, start-ups are associated with different digital intensities using the taxonomy developed by Calvino et al. (2018[56]). In particular, Figure 4.1 plots the increase in the likelihood of acquisition from having a patent or raising an additional dollar in VC (in USD) as a percentage of the average probability of being acquired in the sample.

Figure 4.1. The innovation premium across regions and sectors.

Panel A. Innovation premium across the US and the EU



Panel B. Innovation premium across low- and high-digital intensity sectors



Note: The figure shows the results of the linear probability model using cross-sectional variation Equation 1 for different specifications exploring heterogeneity across start-up targets in the EU27 and the US and low and high digital intensity sectors. In particular, it runs Equation 1 for four different subsamples: (i) only EU companies, (ii) only US companies, (iii) only companies in log-digital intensity sectors, and (iv) only companies in high-digital intensity sectors. For each subsample, the average probability of being acquired is computed. The premium on having a patent is computed as the coefficient of having a patent over the corresponding average probability of being acquired. The premium on raising one million (2011) US dollars in VC is computed by multiplying the coefficient of VC capital times the log of one plus one million and scaling this number by the average probability of acquisition in each subsample.
Source: OECD calculations based on OECD/STI Start-ups Database, OBIRS M&A, and PATSTAT data.

Panels A of Figure 4.1 shows the heterogeneity of acquired start-ups in the EU and the US, highlighting some important differences. First, having a patent is more relevant in the EU. As shown in the main text, acquirors select targets with patents more frequently when acquisitions happen across markets. As cross-country acquisitions are more frequent in the EU (approximately 40% of EU acquisitions happen across countries, mostly involving two EU players), this is reflected in the increased probability of acquisition for firms that have a patent. Second, it shows that the stock of venture capital is positively associated with acquisition in the US but not in the EU. On the one hand, this may suggest the greater role of VC markets in the US vis-à-vis the EU, where greater amounts of VC-financing might entail a stronger quality signal. The VC levels in the EU are much lower than in the US: approximately 45% of start-ups in the EU do not have any VC in the sample, while this number goes down to 30% for US companies. On the other hand, it might also reflect different financing needs or options across regions.

Restricted Use - À usage restreint

Panel B instead compares the premium of having a patent and raising one million dollars in VC across low- and high-digital intensity sectors. As can be seen, having a patent has a similar premium on the probabilities of being acquired across these sectors. In fact, the premium in low-digitally intensive sectors is even slightly higher. Note that these are namely manufacturing sectors, traditionally associated with more patenting activity. However, firms belonging to highly digital intensive sectors tend to have substantially higher VC amounts as compared to companies in low-digital intensity sectors. This indicates that VC markets are more relevant for innovation in high-digital intensity sectors. Also, it likely indicates that these firms carry out intensive R&D activities despite their relatively lower number of patents. Likewise, this pattern also helps to understand the dichotomy between VC funding in the EU and the US. VC funds in the sample are more concentrated in medium and low digital intensity sectors in the EU than in the US. 70% of VC-funded companies are in high digital intensity sectors in the EU while 80% of VC-funded companies in the US are in these sectors.

Acquirors

Following the same steps discussed in the previous subsection, the analysis now shifts the focus to the acquirors engaging in start-up acquisitions. The results are reported in Table 4.3. Specifically, the first six columns show the results of the cross-sectional specification, while the last three columns show the within-firm specification. Among the regressions that exploit variation across firms, the first three columns use a linear probability model where the dependent variable is a dummy for start-up acquisition. The other three columns use instead as a dependent variable the cumulative number of acquisitions per year for each acquiror. This choice is motivated by the presence of serial acquirors, i.e., those that acquire more than once in the sample period, as reported in Table 3.3. Thus, columns 4-6 are estimated using the Poisson pseudo-maximum likelihood estimator, which allows to deal with discrete outcome variables.[30]

The first three columns exploiting cross-sectional variation corroborate the innovative profile of acquirors. The table reports the row “mean dependent variable”, which now indicates the average probability for incumbents to acquire a start-up, and it is again used to interpret the coefficients. The premium in these regressions is computed similarly to the previous exercises. Column 1 shows that acquirors that filed a patent are more than three times (0.0154/0.005) more likely to acquire a start-up than those that do not. Second, columns 2 and 3 restrict to those acquirors that filed a patent and show that the previous result also holds in the intensive margin (approximately 12% of incumbents hold patents): acquirors with more patents are more likely to acquire than those that have less (both weighted and unweighted by citations). Third, the next three columns show that these results hold even when looking at the cumulative number of yearly acquisitions as a dependent variable.[31] Finally, the last three columns exploit variation within the firm. As shown, acquirors that file a patent increase substantially the likelihood of engaging in an acquisition in the next period. Likewise, this finding holds when exploiting the intensive margin. Among patent-filing acquirors, those that experience increases in the number of patents with respect to their average patent levels (both weighted and unweighted) also experience an increased probability of acquiring an innovative start-up.

[30] As opposed to the binary outcome used in the linear probability model, the Poisson regression allows the use of a discrete dependent variable.

[31] For these specifications, the regressions are estimated using the Poisson pseud-maximum likelihood estimator, traditionally used when the dependent variable is a count. The interpretation of the coefficients in this case is that a unit increase in the independent variable will increase the log count by the amount of the coefficient. For instance, column 4 shows that having a patent increases the log count by 1.405 units, which corresponds to acquiring 4 more start-ups (exp(1.405)) than the average firm. This number is reported in the premium row expressed in percentages.

Restricted Use - À usage restreint

Therefore, the evidence suggests that not only acquirors choose start-ups that are actively engaging in innovation activities, but also that acquirors are more innovation-oriented with respect to other incumbents. This suggests that incumbents need a base level of absorptive capacity to acquire start-ups and benefit from their technological infrastructure. Alternatively, it could indicate that technological leaders are the ones engaging in acquisitions, potentially with the goal of preventing disruptive start-ups from growing. In addition, the panel specification indicates that acquirors engage in acquisitions when they are in a phase of technological expansion (i.e., their innovation activity is above its average over time). This contradicts the results of Zhao (2009[28]), who finds that publicly listed US firms acquire incumbent companies during periods of low patenting performance, but aligns with the findings in Bena and Li (2014[15]).

Table 4.3. A description of acquirors – which characteristics make incumbents more likely to acquire?

	Cross-section						Within-firm		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Has a patent}_{t-1}$	0.0154***			1.405***			0.0137***		
	(0.0002)			(0.0276)			(0.0003)		
$\log(1+\text{Patent stock}_{t-1})$		0.0094***			0.368***			0.0060***	
		(0.0004)			(0.0190)			(0.0004)	
$\log(1+\text{Citations}$ $-\text{weighted patent stock}_{t-1})$			0.0076***			0.223***			0.0031***
			(0.0003)			(0.0108)			(0.0002)
Estimation	LP	LP	LP	Poisson	Poisson	Poisson	LP	LP	LP
Only patenting incumbents	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	No	No	No	No	Yes	Yes	Yes
Industry-country-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2 992 702	268 715	268 715	1 192 233	93 972	93 972	3 236 814	342 174	342 174
(Pseudo) R-squared	0.051	0.100	0.101	0.225	0.151	0.154	0.123	0.178	0.178
Mean dep. variable	0.5	1.9	1.9	0.7	3.6	3.6	0.4	1.5	1.5
Premium	322.7	14.2	15.8	562.0	290.3	244.1	311.4	11.4	8.0

Note: The table shows the results of Equation 1 using cross- (first six columns) and Equation 2 within-firm variation (last three columns). The first three and last three columns use the linear probability model where the dependent variable is a dummy for acquisition. The second set of three columns uses as a dependent variable the number of acquisitions in each period and estimates using Poisson ML. The first columns in each set of three show the effect of a dummy variable that takes the value 1 if firm *i* had a patent at time *t-1* on the probability of being acquired (extensive margin). The next two columns in each set of three reflect the effect of the patent stock and citation-weighted patent stock among firms that ever held a patent during the sample period (intensive margin). The average dependent variable reports the unconditional probability of being acquired in the relevant sample or the average count in the case of the Poisson specification. The premium shows the coefficient of interest as a percentage of the mean dependent variable. All regressions control industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%, ^: R-squared in the case of the Poisson regression specifications is Pseudo R-squared.
Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A.

Error! Reference source not found. in the Appendix shows a similar exercise to that of Table 4.3 exploiting differences across acquisitions that happen across and within industries and countries. The patent premium is still stronger when acquisitions happen across industries (334% in column 1 and 320% in column 2) or countries (354% of the average dependent variable in column 3 vs 317% in column 4). Notice that these large premia are completely driven by the large number of incumbents in the control group, which drives the average of the dependent variable closer to 0. In other words, these premia are inflated by the choice of control group incumbents.

Restricted Use - À usage restreint

How are acquiror and start-up pairs targets formed?

After having shown that both acquisition targets and acquirors are more likely to have patents before the acquisition event, this subsection studies the role that markets and technology overlap play in pair formation. In particular, this analysis leverages the framework described in Equation 3 to understand whether industry, country, and patent similarities are important dimensions for pair formation. As explained above, this specification exploits differences across the actual pairs formed in the real business and fictitious deals.

Columns 1 and 3 of Table 4.4 show the median coefficients resulting from one hundred Monte Carlo iterations of Equation 3 in two different specifications. Column 1 shows the result of estimating Equation 3 without the menu-of-deals fixed effect and the randomly formed pairs. The standard errors are the standard deviation of these coefficients across the different Monte Carlo regressions. The first coefficient shows a positive relationship between a formed pair and the technological proximity between the acquiror and the target: acquisitions are more likely to happen the higher the similarity of the patent stocks across technological WIPO fields of acquirors and targets. Also, the magnitude of the effect is economically sizable: the average probability of the pair being formed is increased by approximately 0.5 percentage points in both specifications. By construction, the average probability of a pair forming is one-seventh. This implies approximately a 250% premium on publishing in the same WIPO field as an acquiror on the probability of being formed.[32] This suggests that acquisitions might be strongly motivated by technological reasons and can be a vehicle to access the innovations developed by the start-ups. By the same token, the next two coefficients show that pairs are less likely to be formed when the actors do not share industries or countries. While cross-industry and cross-country acquisitions are also prevalent in the data, acquirors are more likely to acquire within their industries and countries.[33]

These results are consistent with Hoberg and Phillips (2010[32]) who show that acquisitions are more likely to happen when companies share broad product similarities, which they show to be higher between companies within the same 3-digit industries. Similarly, these results align with the ones showcased by Bena and Li (2014[15]). While the results are, again, not directly comparable due to the use of different measures for technological and market overlap, they find that pairs with a higher product market relatedness and technological overlap are more likely to be formed in a sample with cross-industry pairs. These findings hint that product market overlaps and technological synergies are important components in start-up acquisitions.

Columns 2 and 4 of Table 4.4 zooms into the heterogeneous role of technological proximity. Similarly to the previous specifications, Column 2 exploits variation across the randomly formed pairs while Column 4 exploits variation within each set of matched acquirors and targets. The baseline specification is expanded with two new terms that include the interaction between the technological proximity variable and both the cross-industry and the cross-country dummy. It finds that technological proximity plays a more relevant role when pairs are formed across industries: if the pair is cross-industry, it is more important that the companies have patents in related technologies.

This result directly speaks to the result of Bena and Li (2014[15]). In their paper, the authors find that, while technological overlap and product market relatedness both increase the likelihood of pair formation, their interaction has a negative effect. They argue, along the lines of Hoberg and Phillips (2010[32]), that as firms have closer substitutes, gains in an acquisition will only stem from acquiring firms with differentiated technologies. Assuming that industries proxy well for product markets (Hoberg and Phillips, 2010[32];

[32] Where the premium is defined similarly as before: the coefficient over the average dependent variable.

[33] Approximately 70% of acquisitions happen across 3-digit NACE Rev. 2 industries and 20% happen across countries. Note that this does not necessarily mean that firms do not enter other markets through acquisitions, as industries and geography are broad concepts and cross-industry acquisitions are very frequent in the data.

Restricted Use - À usage restreint

Calligaris et al., 2024b[57]) the same logic applies in this paper. First, acquirors that choose to expand to new industries might find it beneficial to acquire companies with similar technologies to leverage their existing knowledge and create synergies. Second, a different technology might threaten the incumbent's position within its market because it may indicate that either the start-up can compete more efficiently in its market or it can produce a more differentiated product, triggering the acquisition in both cases to retain market power.

Table 4.4. Pair formation – how are acquiror and target pairs formed?

	(1)	(2)	(3)	(4)
Technological proximity$_{t-1}$	0.5526***	0.6134***	0.4877***	0.4954***
	(0.0140)	(0.0567)	(0.0079)	(0.0224)
Cross-industry	-0.3313***	-0.3700***	-0.2629***	-0.2841***
	(0.0171)	(0.0192)	(0.0076)	(0.0086)
Cross-country	-0.1824***	-0.1431***	-0.0733***	-0.0577***
	(0.0120)	(0.0130)	(0.0050)	(0.0052)
Technological proximity$_{t-1}$x Cross-industry		0.1137**		0.0645***
		(0.0496)		(0.0204)
Technological proximity$_{t-1}$x Cross-country		-0.1950***		-0.0769***
		(0.0454)		(0.0199)
Sample	Random	Random	Matched	Matched
Menu-of-Deals FE	No	No	Yes	Yes
Observations	23 835	23 835	6 776	6 776
Deals	3 405	3 405	968	968
R-squared	0.2639	0.2650	0.2744	0.2821

Note: The table shows the results of 100 Monte-Carlo simulations for Equation 3 estimated using a linear probability model. The coefficient in the table is the median value of the specified coefficient and the standard errors are the standard deviation of these coefficients across the simulations. The dependent variable is a dummy variable that takes value 1 if the deal took place and 0 otherwise. Technological proximity is the measure of technological closeness à la Jaffe (1986[52]), cross-industry is a dummy variable that takes the value 1 if the target and acquiror pair are in different 3-digit NACE Rev. 2 industries, and cross-country is a dummy variable that takes the value 1 if the target and acquiror pair are in different countries. The row labelled Sample indicates whether the pairs were formed randomly or matching on the VC and age level of the acquired start-up. Columns 3 and 4 include menu-of-deals fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on OECD/STI Start-ups Database, Orbis M&A, and PATSTAT.

Lastly, the interaction term between the technological proximity and the cross-country indicator is also compatible with previous findings as in Hsu et al. (2021[36]), where they find that acquirors resort to technologically-intensive targets from other countries as a way to improve their technological outcomes. The exercise above shows that these technological targets are likely to be more technologically different as well, which might suggest that they have more efficient or differentiated technologies than those of the acquiror.

All in all, the evidence presented in this section suggests that technological firms are more likely to engage in acquisitions. In addition, there is room to think that there are product market and technological synergies that might be advantageous for both parties after the deal culminates. The next sections shows whether these potential synergies are materialised after the acquisition takes place.

Restricted Use - À usage restreint

5 How does acquisition affect innovation?

The previous sections showed that innovation motives may constitute an important factor in the decision of companies to engage in start-up acquisitions, as incumbents with a strong patent portfolio choose to interact with start-up targets that show early signs of innovation activity. Importantly, the fact that transactions are more likely to happen the closer pairs are in the technological space reinforces the idea that acquiring the innovation of the target start-up might be one of the reasons behind the acquisition choice. A natural question follows: what is the effect of these interactions on the acquired and acquiring companies in terms of innovation performance?

Methodology

To answer this question, a difference-in-differences (DID, henceforth) estimator strategy is employed. Specifically, this estimator traditionally compares the outcome of interest (patenting activity) of treated units (acquired start-ups or acquiring incumbents) with the outcome of interest of control group units (non-acquired start-ups or non-acquiring incumbents) before and after the treatment (acquisition). The DID estimator is unbiased as long as differences in the outcome of interest would have remained constant across treated and control groups if the treatment had not happened (Abadie, 2005[58]). In this specific setting, it means that the coefficient of interest is properly estimated if the differences in patenting activity observed in the pre-acquisition phase between treated and non-treated would have remained constant across time in the absence of an acquisition.

In practice, a popular method to estimate the so-called average treatment effects is to use two-way fixed effects (TWFE) regressions to get an estimate of the DID estimator.[34] However, recent research shows that the use of TWFE to estimate average treatment effects requires additional assumptions on the nature of the treatment for it to be unbiased (Borusyak, Jaravel and Spiess, 2024[59]). Particularly, the effect of the treatment should be constant over time and treated units, which is a hardly met assumption in this setting.[35] On the one hand, firms are treated at different periods. On the other hand, the effect of the treatment is likely to be heterogeneous across periods and firms (e.g., acquirors that purchase different amounts of start-ups).

[34] See Wolfers (2006[73]) for a famous application.

[35] The problem with using TWFE estimators to get the unbiased DID estimate is that this methodology runs into what is called *forbidden comparisons*. Simply put, the TWFE estimator fails to get unbiased estimates of the DID estimator because it is the average of two kinds of comparisons (Goodman-Bacon, 2021[72]). First, the estimator compares the outcomes of treated and non-treated or not-yet-treated units, which are generally unproblematic. However, a second term uses differences between early- and late-treated units (when treatment timing differs) or less and more treated units (in the case of a discrete or continuous treatment). This second term is the one that generates a bias when using the typical TWFE estimation.

Restricted Use - À usage restreint

As a response to this problem, a plethora of estimators that avoid these biases have been developed.[36] Among the many estimators proposed to deal with staggered treatments with heterogeneous effects (Callaway and Sant'Anna, 2021[60]; Sun and Abraham, 2021[61]; Borusyak, Jaravel and Spiess, 2024[59]; de Chaisemartin and d'Haultfoeuille, 2021a[62]), this paper relies on the methodology developed by de Chaisemartin and D'Haultfoeuille (2024[63]), since it accommodates best all the necessary cases that are present in the data.[37] First, it allows the estimation with binary and staggered treatments. These are particularly relevant when analysing start-up targets, as they are usually acquired only once (binary) but in different years (staggered). Second, it also accommodates discrete staggered treatments, which is relevant in the case of acquirors since some of them repeatedly engage in start-up acquisition. Unlike the traditional DID estimator, this methodology also allows to compute DID estimates without a never-treated group by exploiting variation across not-yet-treated and treated units. The analysis below exploits this variation to control for the selection across treatment and control groups shown in the previous sections.

Two different exercises are performed to provide evidence of how an acquisition can affect subsequent innovation. In the baseline exercise, the same sample of acquired start-ups as in the previous section is used. As shown in the previous section, firms with more patenting activity are more likely to be acquired. This selection bias makes it challenging to accurately identify the effect of acquisition on patenting activity, as it implies that acquired and control group start-ups are inherently different in terms of patenting performance. Consequently, other factors beyond the acquisition itself might be correlated with the different innovation performance observed after the acquisition. To address this selection bias, the main specification restricts the control group to not-yet-treated companies, that is, companies that will be acquired (will acquire) but have not been acquired (have not acquired) yet. Additionally, the date of announcement of the acquisition is used instead of the date of its completion to control for anticipation effects that might bias the estimates. The results remain robust when using the never-acquired start-ups as a control group and also when using propensity score matching to create a comparable control group of never-acquired start-ups. These results are shown in Figure 6.2 in the Appendix.

Additionally, the analysis uses the approach suggested by Bena and Li (2014[15]) to control for this selection bias and the potential endogeneity of acquisition and innovation decisions. In their paper, the authors compare the patenting performance of acquired companies with that of companies that received acquisitions bids but these were withdrawn for reasons exogenous to innovation. Under this circumstance, the assignment of the treatment across treated (i.e., completed deals) and control sample (i.e., bids withdrawn due to reasons exogenous to innovation) can be treated as good as random, therefore ruling out any section concerns and providing a causal impact of the acquisition on innovation outcomes. Following this rationale, the analysis below shows how start-ups with withdrawn bids perform after the withdrawal vis-à-vis the control group start-ups and compares this difference to that between acquired start-ups and control group start-ups after acquisition. In other words, the analysis exploits a triple DID estimator to tackle endogeneity concerns by comparing the ex-post performance of start-ups with withdrawn and successful bids vis-à-vis never-acquired start-ups.[38]

The Orbis M&A database identifies 457 withdrawn bids in the sample of countries and years covered in the analysis. To determine whether the discontinuation of these transactions happened for reasons unrelated to the innovation performance of the target, online news on the withdrawn acquisitions is surveyed. The different reasons for withdrawal are classified, and only the ones that are exogenous to

[36] See de Chaisemartin and D'Haultfoeuille (2023[71]) for an extensive literature review.

[37] Note that reassuringly all the results of this section and the results reported in the next section on the effects of CVC investments on start-up innovation continue to hold when using any of these alternative methodologies: Callaway and Sant'Anna (2021[62]); Sun and Abraham (2021[63]); Borusyak, Jaravel and Spiess (2024[61]).

[38] Alternatively, the results remain unchanged when simply using the group of start-ups with withdrawn bids as a control group.

Restricted Use - À usage restreint

innovation strategies are selected. Namely, the exercise regards as exogenous with respect to innovation performance those acquisitions withdrawn due to competing bids (and not followed by another acquisition), macroeconomic conditions, or objections by regulatory bodies. Those related to differences in opinions about the valuation of companies, growth strategies, or disagreements among owners are left out as they could potentially correlate with the innovative performance of companies. This leaves 122 bids for start-ups that were withdrawn due to reasons exogenous to innovation, spanning 14 countries and 46 3-digit NACE Rev. 2 industries.[39] In this robustness exercise, the regressions are only performed on those country-industry combinations for which there is at least one withdrawn bid. This leaves 6 725 acquired start-ups and 5 091 acquirors active in these country-industry combinations.[40] On the incumbent side, acquirors are restricted to single-time acquirors, i.e., incumbents that engage only with one start-up acquisition, controlling also for acquisitions of other incumbent firms.[41] For the control group, the sample is restricted to companies involved only with the withdrawn deal and no other acquisition of start-ups or other incumbent firms.

Acquired start-ups

This subsection looks at the post-acquisition innovation performance of start-ups. Figure 5.1. The effect on the number of patents filed and patent citations by acquired start-ups.Figure 5.1shows the average treatment effects of acquisitions on the flow of patent counts (Panel A) and the citation flows (Panel B) using the full sample of acquired start-ups on the left-hand side panels. Likewise, the right-hand side panels restrict the control group to start-ups that received a bid withdrawn for reasons exogenous to innovation to provide a causal relationship. Each coefficient of each panel represents the change in the difference in patenting flows between not-yet-acquired and acquired companies between the period preceding the acquisition *t=0* and the period of interest *t*. In addition, the variable of interest has been normalised by its average value across start-ups before the acquisition (if any) to ease interpretation. Therefore, a point estimate of *x* at time *t* should be interpreted as a change in the difference of patenting flows between *0* and *t* equivalent to *x* times the unconditional average patent flow.[42]

Panel A shows that while the differences between control and treated groups in patenting performance are constant before the acquisition, the number of patents filed by acquired start-ups decreases relatively more after the acquisition takes place. This evidence points to a negative effect of acquisition on the innovation performance of the target (Stiebale and Reize, 2011[47]; Stiebale, 2016[48]; Cunningham, Ederer and Ma, 2021[21]; Altomonte, El-Mallakh and Sonno, 2024[33]). In terms of magnitude, the decrease is not only statistically significant but also economically sizable. The difference in the standardised flow of yearly patents decreases by approximately 1.5 times the unconditional average yearly flow over the time horizon

[39] From the 457 initially withdrawn bids between 2001 and 2021 involving the start-ups in the dataset, 35 were withdrawn due to disagreements in growth strategies or between stakeholders, 44 were withdrawn due to disagreements over the valuation of the transaction, 18 were withdrawn due to negative developments involving one of the parties, and for 238 bids were withdrawn for unclear reasons. This leaves 122 exogenously withdrawn bids (31 due to competing bids, 56 due to adverse macroeconomic conditions, and 35 due to opposition from regulatory bodies or failing to comply with their requirements).

[40] Given that this restricted sample is different from the extended sample used in the baseline exercise in terms of countries covered, sample size, and so on, the analysis should be interpreted with caution and bearing in mind the sample constraints.

[41] Approximately 20% of acquirors active in these industries and countries remain after this restriction is applied.

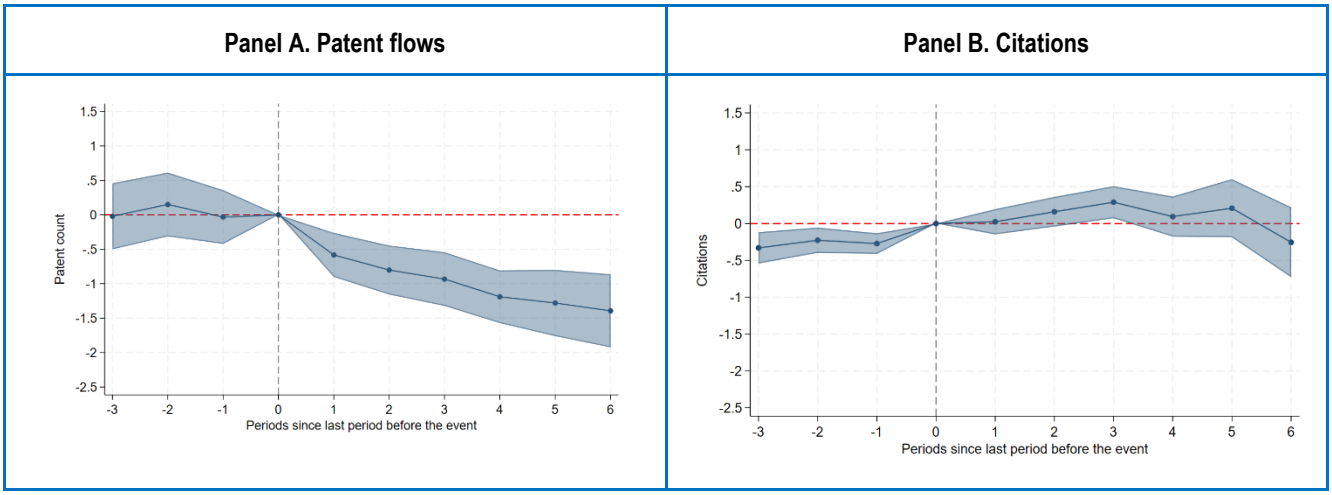
[42] The baseline specification follows acquired start-ups (acquiring firms) from 4 years previous the acquisition event until 5 years afterwards. Note that, as a robustness, different time intervals for the computation of pre-trends and ex-post effects are considered. Results remain unchanged when expanding the time frame considered.

Restricted Use - À usage restreint

considered (where the average unstandardised patent flow corresponds to 0.6 patents, therefore resulting in a reduction of 0.9 patents).

Panel B shows the equivalent exercise for the evolution of citations. While the previous panel was informative about the rate at which start-ups patent new ideas and their quality, this panel reports the number of citations received per year, which is informative about the use of both old and new technologies. After the acquisition, they likely capture namely the use of innovation patented before the acquisition, given the sharp decline in the patent count observed in Panel A. As can be seen, the evolution of citations does not present any abnormalities around acquisition, but they evolve slightly increasing relative to those of control group firms. Nevertheless, notice that while control group start-ups receive citations from new and old technologies, acquired start-ups mainly receive citations from old technologies due to the sharp decline found in Panels A. For the differences across them to stay constant, citations to old innovations of acquired start-ups should compensate for the absence of new patented inventions. This is further corroborated by two pieces of evidence. First, there is a pronounced increase in the share of patenting firms that do not patent ever again when we use as a dependent variable a dummy for patenting in a specific year. This can be also seen from the descriptive statistics presented in Table 3.2. Second, distinguishing between inventions patented before and after acquisition shows that citations to new inventions drop dramatically after the event.[43] This evidence might suggest that the acquisition boosts the diffusion of the old innovations produced by the acquired start-up. However, citations fall as the company stops publishing new patents after the acquisition. As older patents become obsolete, they receive fewer citations relative to innovations from non-acquired start-ups, which receive citations mainly from new innovations.

Figure 5.1. The effect on the number of patents filed and patent citations by acquired start-ups.



Notes: The figure shows the difference in the number of applied inventions in Panel A and in the number of citations in Panel B of acquired companies vis-à-vis not-yet-treated start-ups using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[63]). All panels use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.

Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A.

The analysis follows by performing the causal analysis outlined above relying on the exogenously withdrawn bids. Figure 5.2 shows the ex-post patenting performance of acquired start-ups and start-ups whose bids were withdrawn vis-à-vis never-acquired start-ups using the de Chaisemartin and

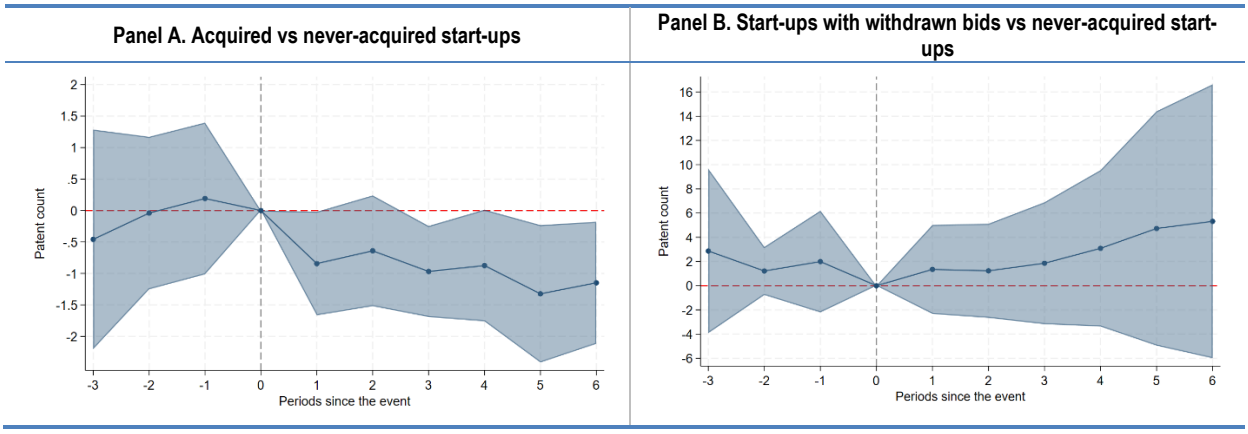
[43] The figure remains virtually unchanged when restricting to only citations to patents filed before the acquisition.

Restricted Use - À usage restreint

D'Haultfoeuille (2024[63]) DID estimator. In particular, Panel A shows how patents filed by acquired start-ups perform after the acquisition announcement relative to never-acquired start-ups. Meanwhile, Panel B shows how start-ups that received an acquisition bid that was withdrawn for reasons exogenous to innovation perform after the withdrawal against the same control group of start-ups. The difference in coefficients across both figures yields effectively a triple DID estimator which compares the evolution of acquired start-ups with that of start-ups whose bids were withdrawn (all relative to control group start-ups) (Olsen and Moen, 2022[64]).[44]

To validate this identification strategy, the analysis performs several checks before addressing the DID estimates. Table 6.3 and Figure 6.3 in the Appendix show differences in patenting performance across start-ups that received withdrawn bids and start-ups that were effectively acquired. Table 6.3 shows that the results of a regression in the same fashion as the previous ex-ante exercise. In this case, the exercise uses only the acquired start-ups in the moment of acquisition as treated units and the start-ups whose bids were withdrawn in the moment of withdrawal as control group. The results indicate that the flow of patents and their citations are similar across acquired start-ups in the moment of acquisition and start-ups whose bids were withdrawn in the moment of withdrawal. Likewise, Figure 6.3 shows the average patent flows of acquired start-ups and start-ups with withdrawn bids around acquisition or withdrawal. As can be seen, the evolution of the average patenting flows is identical across both groups before the announcement of an acquisition. However, acquired start-ups experience a decline in the patenting flow following an acquisition that is not as pronounced for start-ups whose bids were withdrawn after withdrawal.

Figure 5.2. The effect on the number of patents filed by acquired start-ups using an exogenous shock.



Notes: This figure shows the difference in the number of applied inventions in Panel A between acquired companies vis-à-vis not-yet-treated start-ups using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[63]). Panel B shows the equivalent exercise for start-ups whose bids were exogenously withdrawn but the treatment takes value 1 after the withdrawal of the bid. All panels use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A.

[44] The equivalence between two difference-in-difference estimators and a triple diff-in-diff has been proved in the literature (Olsen and Moen, 2022[66]). However, there is no formal proof in the context of the de Chaisemartin and D'Haultfoeuille (2024[65]).

Restricted Use - À usage restreint

Figure 5.2 shows the results of the exercise using the DID strategy outlined above. Panel A shows the differences between acquired start-ups and control group start-ups, restricting to countries and industries with at least one withdrawn bid. As can be seen, the negative effect on the patent flow persists in this sample with a similar magnitude to the one found when using all acquired start-ups and the not-yet-treated as a control group. Likewise, Panel B compares the differences over time between start-ups with withdrawn bids to control group start-ups before and after the withdrawal of the bid. While acquired start-ups experience a strong negative decline, the effect of the bid withdrawal on the start-ups in Panel B does not seem to statistically affect the outcomes of these companies. As mentioned above, the difference between both coefficients yields the triple DID estimate of the effect of a successful bid after controlling for selection and endogeneity. Assuming the effect on the withdrawn bids is zero as suggested by Panel B, the estimate of the triple DID is equivalent to the coefficient stemming from Panel A. Testing for the pre-trends allows to rule out differential behaviour across these two groups of companies.[45]

The evidence above seems to suggest that acquisitions harm start-up innovation. Despite the acquired start-ups being more innovative and producing better quality innovations before the deal, their innovation performance worsens after the acquisition takes place. Nevertheless, it is not possible yet to assert conclusions on the innovation performance without analysing the acquiror side. A possibility is that, upon acquisition, patenting activities are centralised in the parent company, which might for example start appropriating the innovations developed by the acquired start-up. In this case, some of the innovation outcomes of the start-ups would not be observed, potentially providing a misleading message from the patterns observed in the figures above. This is what Stieable (2016[48]) suggests in the context of cross-border acquisitions. The next subsection tries to answer this question performing the same exercise for acquiror companies.

Acquirors

As mentioned above, acquiror innovation outcomes should not improve after acquisition to unequivocally assert that start-up innovation is stifled after the event. Figure 5.3 shows the DID estimates on the patent count in Panel A. This exercise exploits the number of acquired start-ups each period as treatment, controlling for the number of acquisitions that happen outside the sample (i.e., taken from Orbis M&A and referring to non-start-ups).[46] In other words, the treatment is modelled as a discrete variable that takes the value of the cumulative number of start-ups acquired over the sample period. As can be seen, there are no significant effects on either of the patent-count measures (Panel A) or the flow of citations (Panel B).

Figure 5.4 shows the results of the exercise that relies on the exogenously withdrawn bids. These panels restrict the sample to the incumbents that acquire only one start-up over the sample period (excluding also those that acquire other firms from Orbis M&A, i.e., non-start-ups).[47] Likewise, control-group incumbents are restricted to those that operate in industries and countries in which there is at least one withdrawn bid. Panel A compares the evolution of the patent flow across acquirors and incumbents that never engaged

[45] The paper uses the equivalence between two diff-in-diffs and the triple diff-in-diff due to the use of the **did_multiplegt_dyn** command in STATA to implement the de Chaisemartin and D'Haultfoeuille (2024[65]) which does not allow for interaction terms of the treatment.

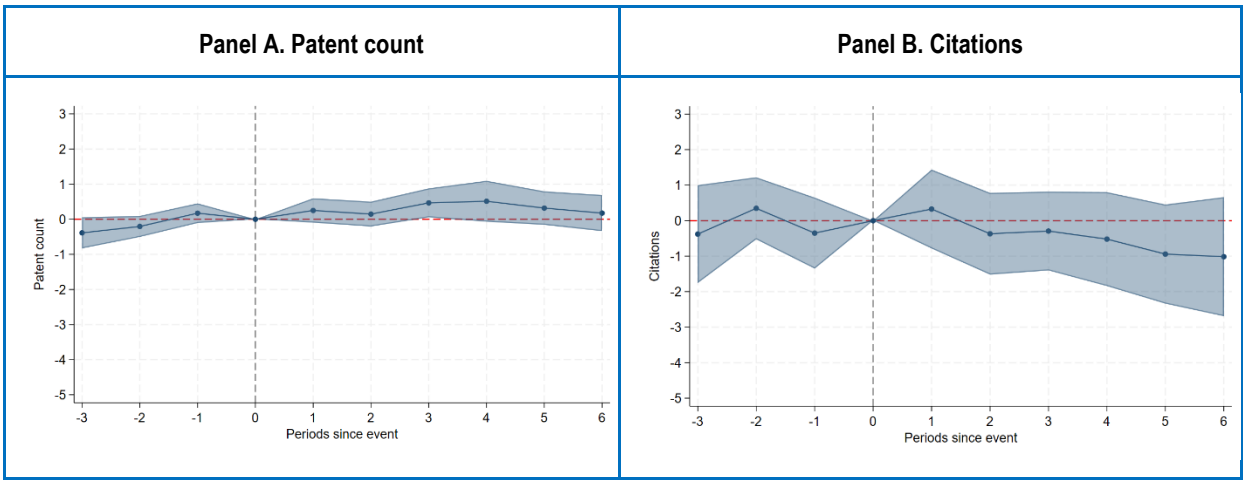
[46] There are several ways in which the treatment can be modelled in the case of the acquiror. Acquirors are more complex to analyse than start-ups because acquisition can take place in several periods or even several times within the same period. In addition to the exercise shown in the main text, in a robustness exercise, acquisition is modelled also as a binary treatment that switches on when there is at least one acquisition and switches off when no acquisition takes place. The results are qualitatively the same to those reported in the paper and are available upon request.

[47] Note that the results reported in panel A and B remain valid when focusing only on this sub-sample of acquirors (but considering the full control group).

Restricted Use - À usage restreint

in an acquisition. Panel B compares the evolution of the patent flow across acquirors who eventually withdrew a bid and incumbents in the control group. The difference in the coefficients across both specifications yields the triple DID estimator of interest. As can be observed, neither the successful nor the unsuccessful bidders experience a differential evolution in their performance following an acquisition or the withdrawal of a bid. This finding, again, corroborates the evidence presented in Figure 5.3 by confirming the lack of effect on the patenting activity of acquirors.

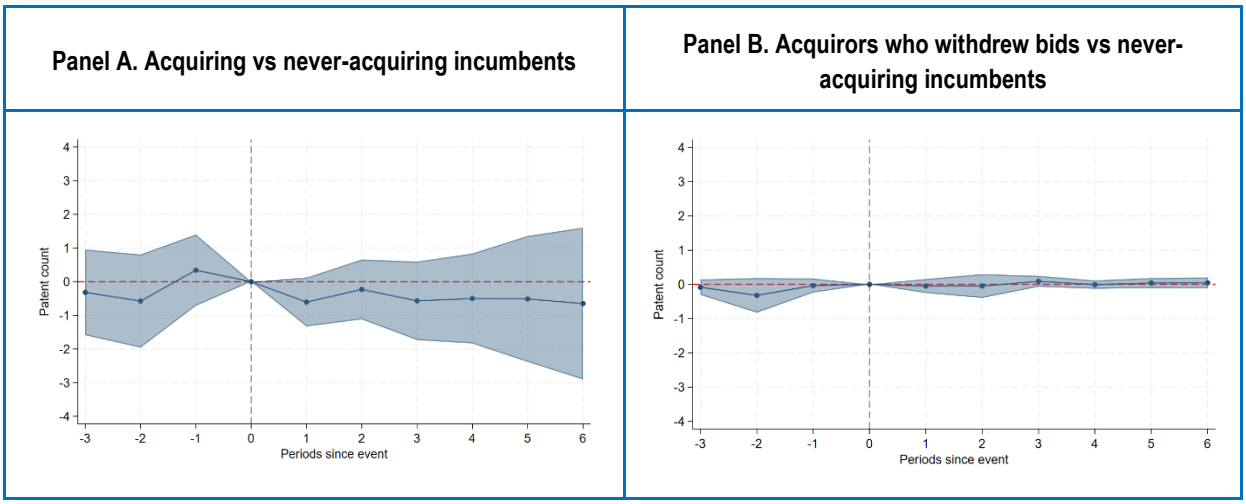
Figure 5.3. The effect on patent filings and patent citations of acquirors



Notes: The figure shows the difference in the number of applied inventions and the yearly flow of citations in Panels A and C, respectively, of acquired companies vis-à-vis those not-yet-treated start-ups using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[63]). All panels use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.

Source: OECD calculations based on data from PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

Figure 5.4. The effect on filed patents of acquirors using an exogenous shock



Notes: The figure shows the difference in the number of applied inventions across single-time acquiring incumbents and never-acquiring incumbents in Panels A and and the difference between incumbents who withdrew a bid and never-acquiring incumbents in Panel B, using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[63]). All panels use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.

Source: OECD calculations based on data from PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

All in all, the findings in this section corroborate studies that find a negative effect on the innovative activity of the merged pair, as in Haucap, Rasch, and Stiebale (2019[43]). Contrary to Stiebale (2016[48]), this paper does not find that the acquirors' patenting activity compensates for the loss of activity in their targets.[48] In addition, an analysis of the pair-specific outcomes shows that the results are dominated by the acquiror's outcomes in that the findings do not show any impact of acquisitions on the patenting activity of the merged entity. Therefore, it is concluded that it is unlikely that target innovation decreases due to a shift of patenting activities from the start-up to the corporate parent. Overall, the evidence reported so far suggests that acquisitions are strongly driven by innovation motives, but that they are not a catalyst for follow-on innovation activity.

Potential underlying channels

The evidence reported so far shows a strong decline in patenting activity of acquired start-ups, not compensated by an increase in patenting of their acquirors. Several explanations can be proposed to explain this outcome.

First, a decline in patenting activity may not necessarily reflect a decline in innovation, as not all innovations are protected by patents. The patenting activity of companies reflects not only their technological advancements but also their strategic behaviour (Veugelers and Schneider, 2018[65]). In other words, the target's patenting activity may decline because its intellectual property (henceforth, IP) strategy changes post-acquisition, opting for greater secrecy in the innovation process. In this case, actual innovation may not decline after the transaction, even if patent filings decrease. Alternatively, the decline could result from the completion of the development stage of the innovation process and the onset of the commercialisation of the inventions patented prior to the acquisition. From this perspective, a decline in patenting activity does not necessarily signify reduced innovation; instead, it might simply reflect a transition to the final stage of the innovation life cycle.

However, if the decline in patenting activity does indeed reflect a decline in innovation, the question is what drives this decline. On the one hand, it could be that target companies have no intention of disrupting the market in the long run, but only patent ideas that are complementary to incumbents to make themselves more appealing for acquisition. Once they cash out, they may lack further incentives to continue innovating (*innovation-for-buyout*). On the other hand, incumbents might acquire young and promising start-ups to prevent future competition in the long run, seeking to neutralise the potential threats to their dominant positions (*killer acquisitions*). Finally, the reduction in innovation performance could simply result from inefficiencies in the interactions between the acquired start-up and its new parent company, rather than being driven by any strategic motives. It is also worth noting that these explanations are not mutually exclusive and could coexist.

[48] Notice, however, that Stiebale (2016[50]) restricts acquirors to single-time acquisitions. By employing the methodology developed by de Chaisemartin and D'Haultfoeuille (2024[65]) that allows for discrete treatment, the present paper includes in the analysis the "serial" acquirors, and therefore offers a complete picture of incumbents' activities.

Restricted Use - À usage restreint

This subsection provides *suggestive evidence* on the possible channels discussed above to understand whether some of them are more likely to apply.

Table 5.1 explores whether the decline in patenting activity can be interpreted as a decline in innovation. To do this, the paper first delves into the heterogeneity across acquisitions performed by acquirors with different levels of patents, which might reflect different IP strategies followed by acquiring firms. For instance, a more pronounced decline might be observed among firms acquired by companies that either do not patent or patent very little. This could indicate that innovation continues but that the acquiring company does not rely on formal IP as a strategy to protect its innovation. To investigate this, acquiring firms are categorised into two groups based on whether their number of filed patents is above or below the median.[49] Then, the sample of acquired start-ups is divided according to whether their acquiror was above or below the median number of patents filed. The patenting performance of these two groups of acquired start-ups is then analysed using the framework outlined in this section.

Table 5.1 reports the results. Specifically, the first row shows the average ex-post effect of the acquisition on the patent flow of the target in the years following the event. The second and third rows show the test for the joint nullity of the ex-post effects and the pre-trends, respectively. In particular, the second row shows whether the differences across treatment (acquired) and control (not-yet-acquired) start-ups change after the acquisition. Likewise, the third row shows whether the change in differences is different from zero before the acquisition period. In other words, they test whether the differences across treatment and control groups change after the acquisition, and whether they were already changing before, respectively. The first two columns in Table 5.1 show the average DID estimate of the effect of the acquisition on the patent flow of the target, distinguishing between those acquired by incumbents with below- and above-median patenting activity. As shown, acquisitions have a negative impact on innovation in both columns. However, the impact is stronger among those targets acquired by incumbents who patent frequently. In fact, the impact on start-ups acquired by incumbents who do not patent frequently, and, thus, are more likely to be more secretive about their innovation, loses significance relative to the baseline. Therefore, differential IP strategies do not seem to explain the observed reduction in patenting activity.

Second, data on trademarks and sales are analysed to determine whether the reduction in patenting is related to the commercialisation of past innovations. One could expect a positive impact on trademark activity or sales of an acquisition if the acquired start-up can leverage the acquiror's market infrastructure. Column 3 of Table 5.1 uses as a dependent variable the standardised yearly flow of trademarks registered by the start-up (normalised by its average value).[50] There is a statistically significant negative impact of acquisition on registered trademarks. This effect is also economically sizable, as the decrease is equivalent to approximately 50% of the average standardised trademark flow. Moreover, columns 4 and 5 use a restricted sample of 2 712 acquirors and 1 521 targets for which there is available information on gross output in Orbis.[51] They show that the sales of both the acquiror and, particularly, the target, decline by approximately 20 and 40 percent after the acquisition, respectively. Despite the existence of pre-trends, targets go as far as having a 70% decline in sales after 6 years.[52] The combination of results presented in columns 3-5 suggests that acquired start-ups experience a substantial decline in their commercial

[49] For this classification, all acquirors across countries and industries are pooled to compute the median value. However, conditioning on the within country and industry median does not change the results.

[50] Similarly to patenting, different sectors and IP offices might have different traditions regarding registered trademarks. For this reason, the paper standardises the trademark count by the number of trademarks granted in a given IP office and year. To ease the interpretation of this variable, the measure is further normalised by its unconditional average value in the sample used in the regression.

[51] The results of the main analysis hold for this subsample of companies.

[52] The presence of pre-trend is likely due to anticipatory effects: sales and trademarks present a decline in the period before the acquisition is announced, but otherwise the trend between the other pre-periods is flat.

Restricted Use - À usage restreint

performance, which is not offset by an improvement in the acquirors' performance. Stated differently, this evidence suggests that the target's technologies do not seem to be leveraged by their acquirors and yield better commercial performance.

Alternatively, innovations developed by the start-ups could be incorporated into the acquiror's technology or create synergies with the acquiror's assets, leading to an increase in its productivity. Despite that no increase in patenting is observed, a rise in productivity might suggest that the target and its acquiror are experiencing the benefits from the aforementioned synergies and complementarities. Columns 6 and 7 in Table 5.1 show the effect of the acquisition on the target and acquiror's TFP, respectively, using the restricted sample with Orbis information. In both cases, a statistically significant reduction in TFP is observed following the acquisition (approximately 4 and 8% for targets and acquirors, respectively).

Taken together, these correlations do not provide any supporting evidence for the hypotheses mentioned above, suggesting instead that the decline in patenting activity observed in the previous sections is likely a real decline in innovation.

Table 5.1. Can the decline in patents be interpreted as a decline in innovation? – Exercises exploring the channels behind the decline in patenting

	IP Strategies		Commercialisation			Productivity	
	Acquiror has patents below the median	Acquiror has patents above the median	Target's trademarks	Target's log(Sales)	Acquiror's log(Sales)	Target's log(TFP)	Acquiror's log(TFP)
Average effect on the variable of interest after acquisition	-0.9557 (0.6948)	-2.023*** (0.4937)	-0.4784*** (0.1148)	-0.4025*** (0.0286)	-0.2308*** (0.0581)	-0.0408 (0.0302)	-0.0813* (0.0507)
Test joint nullity of the effects (p-value)	0.1347	0.0009***	0.0000***	0.0000***	0.0000***	0.0014***	0.0022***
Test joint nullity of the pre-trends (p-value)	0.2800	0.3962	0.0074**	0.0000***	0.9004	0.1467	0.1200

Notes: The table shows the evolution of different variables using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[63]). All columns use announcement dates. The dependent variable in columns 1, 2, and 3 is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on data from PATSTAT, Orbis, Orbis M&A, the OECD/STI IP Database, and the OECD/STI Start-ups Database.

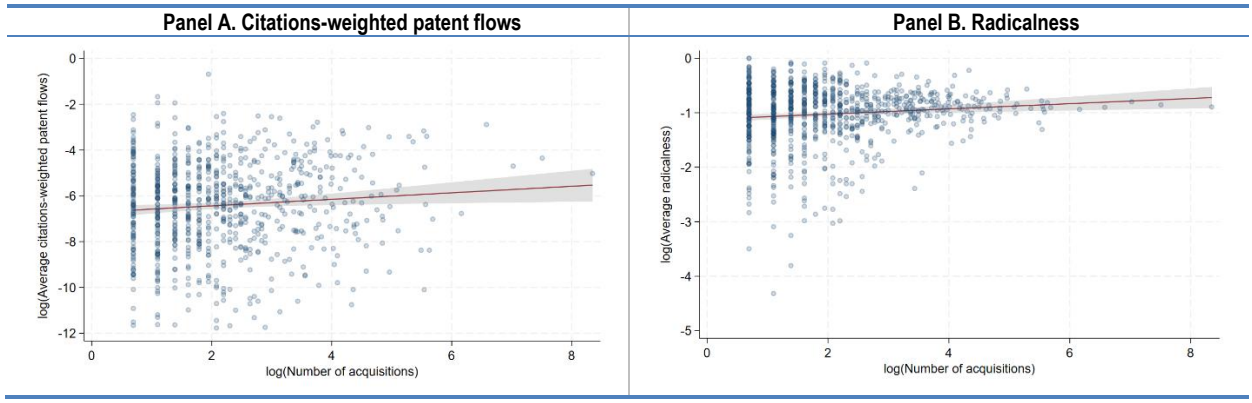
Shifting to possible explanations reflecting a decline in innovation, another hypothesis is related to *innovation-for-buyout*. According to this view, the start-up caters its inventions to incumbents to be acquired and, therefore, focuses on more incremental technologies that complement them. Once a start-up is acquired, it loses the incentive to perform further innovations after cashing out its benefits, and innovation declines. To explore whether target firms tailor their inventions to attract potential acquirors, the paper examines the relationship between acquisition activity and patenting quality. Several papers show that start-ups tend to focus on more incremental (rather than disruptive) innovations when an acquisition becomes a more likely exit strategy (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[22]; Wang, 2018[35]; Warg, 2022[23]; Weiss, 2023[30]). Therefore, one would expect that in markets where acquisitions are more common, patent quality might be lower. In this context, the paper uses the average citation-weighted patent flow of each firm as a measure of patent quality. Alternatively, it also explores the relationship between patent radicalness and the M&A activity in a sector and country. In particular, patent radicalness is defined

Restricted Use - À usage restreint

as the number of technological classes that a patent cites but to which it does not contribute.[53] In other words, it is a measure of how a patent is able to take technologies from different technological classes and incorporate them into another.

Along the lines of this reasoning, Panel A in Figure 5.5 shows the relationship between the number of acquisitions in a specific 3-digit industry and country and the average quality of patents held by the acquired start-ups, as measured by the average 5-year forward citations of their pre-acquisition patent flows. Panel B shows the equivalent exercise using patent radicalness as the dependent variable.[54] There is a positive correlation between the number of acquisitions and the quality of the inventions of the acquired start-ups, both measured through radicalness and citations-weighted patent counts, which contradicts the innovation-for-buyout hypothesis. Start-ups do not seem to focus on more incremental innovation in markets with a high number of acquisitions. Instead, acquisitions seem to concentrate on markets where start-ups are more innovative, suggesting that innovation-for-buyout is unlikely to explain the results in the paper. Rather, incumbent firms seem to acquire more frequently when the start-ups pose potentially a greater threat to their dominant position.

Figure 5.5. Do start-ups innovate to cash out rather than disrupt the market?



Note: The figure shows the scatter plot between the (log) total number of acquisitions in a specific 3-digit industry and country and the (log) average citation-weighted number of patents of acquired companies before acquisition in a specific 3-digit industry and country. The predicted line in Panel A is given by y = -6.7239*** + 0.1424** X while the predicted line in Panel B is given by y=-1.1195*** + 0.0477*** X.
Source: OECD calculations based on PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

Finally, the analysis provides additional suggestive evidence for the killer acquisitions hypothesis by exploiting heterogeneity across markets. If the killer acquisition channel is at play, one would expect the effects of the decline in patenting activity to be stronger when firms share a market (an industry or, to a smaller extent, the same geographical market) than when they do not. While there can be reasons to suppress competitors in other markets (e.g., to expand into a market niche), the incentives for killer acquisitions are greater when firms share a market. To test this, the analysis exploits differences between acquisitions that happen across and within industries and countries, which in this context will proxy for markets. Columns 1 and 2 of Table 5.2 show the DID estimate of the effect on patenting activity of

[53] In this context, technological classes refer to 4-digit IPC families, which are much more disaggregated than the technological classes used to compute the measures of technological proximity.

[54] These two exercises present the result of a simple regression of the (log) average quality and average radicalness on the (log) number of acquisitions. Controlling for industry and country fixed effects (not interacted) increases both the significance and the magnitude of the coefficients even further.

Restricted Use - À usage restreint

acquisitions that happen within and across 3-digit industries. As expected, the reduction in patenting activity experienced by acquired start-ups is stronger for within industry acquisitions. Columns 3 and 4 repeat the analysis, examining acquisitions within and across countries, respectively. Similarly, acquisitions that happen within the same geographic market lead to a more negative correlation between patenting activity and the acquisition event than cross-country acquisitions, even though differences are smaller than in columns 1 and 2. Finally, columns 5 and 6 examine acquisitions that happen within the same industry and country and acquisitions that happen across different industries and countries. The rationale is that firms in the first group are likely to share a product market, as they are in the same industry and geography. In line with the killer acquisition hypothesis, the effect is almost twice as large for acquisitions within the same industry and country relative to those that occur across both dimensions. Nevertheless, it is worth highlighting that the decline in patenting activity happens across all types of acquisitions. Lastly, it is also worth highlighting that while existing literature finds that the technological proximity across pairs influences the post-acquisition outcomes, the findings in the present sample suggest that the effect is similar across pairs with different technological similarities.[55]

Table 5.2. Heterogeneity across countries and industries

	Industries		Countries			
	Within	Across	Within	Across	**Within industries and countries**	**Across industries and countries**
Average cumulative effect from t to t+6	-2.1911*** (0.5978)	-0.9989*** (0.2153)	-1.2960*** (0.5002)	-0.8762*** (0.1764)	-2.0306*** (0.7811)	-0.7674*** (0.1653)
Test joint nullity of the effects (p-value)	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Test joint nullity of the pre-trends (p-value)	0.3958	0.6112	0.9193	0.6075	0.2788	0.7473

Notes: The table shows the evolution of the standardised yearly patent count flow using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[63]). All columns use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects. Standard errors in parentheses. ***: p-value < 1%, **: p-value <5%, *: p-value < 10%.
Source: OECD calculations based on data from PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

Overall, the various analyses conducted do not provide evidence on the hypothesis that a decline in patenting activity does not reflect a decline in innovation. Furthermore, when exploring some channels potentially related to this decline in innovation, the results are consistent with the killer acquisition hypothesis, whereby incumbents acquire young and innovative start-ups within their market to prevent future competition. It is important to note that the analysis presented in this subsection provides only suggestive evidence of the possible mechanisms at play, and further research would be required to establish a causal relationship.

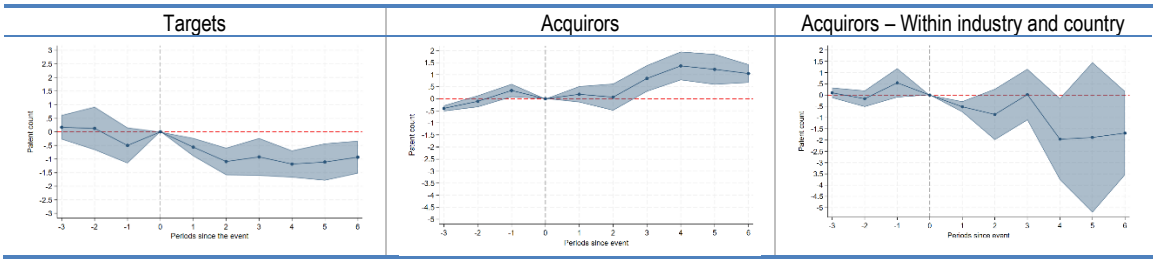
[55] In particular, Altomonte, El-Mallakh, and Sonno (2024[35]) find that technological proximity influences negatively the target's outcomes, while Bena and Li (2014[15]) find the opposite. By contrast, this paper does not find any differential effects across different levels of technological proximity.

Restricted Use - À usage restreint

Box 5.1.The effect of acquisitions in the EU

This box analyses the evolution of patenting activity for EU start-ups and acquirors. The number of papers looking into acquisitions in the EU is scarce, and the overall results suggest that there is a negative effect on the target's patenting activity (Stiebale and Reize, 2011[47]; Stiebale, 2016[48]) and TFP (Gregori, Martinez-Cirello and Nardo, 2023[66]). In this context, Stiebale (2016[48]) shows that the decline in the patenting activity of the target is more than compensated by an increase in the patenting activity of the acquiror in the context of cross-border acquisitions, while the rest of the papers do not provide evidence on both sides of the transaction.

Figure 5.6. The effect of acquisitions on target and acquiror patenting in the EU



Note: The figure shows the evolution of the standardised yearly patent count flow using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[63]). All columns use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on PATSTAT, Orbis M&A, and OECD/STI Start-ups database.

Figure 5.6 shows the baseline specification for start-ups and acquirors in the EU in the first two panels (irrespectively of the origin of their acquirors and target start-up, respectively) and the evolution of the patenting activity of acquirors that engage in within-industry and within-country acquisitions in the last panel (so, by definition, transactions within EU countries). Along the lines of the papers mentioned above, this paper finds that in the EU there is a negative impact of acquisitions on the target's patenting performance (first panel). In particular, the difference between not-yet-acquired and acquired start-ups increases by one time the average flow of patents in the sample. This finding is consistent and similar in magnitude when restricting the sample of acquired start-ups to those happening across and within industries and countries. However, acquirors observe a relatively large increase in their patenting activity, also equivalent to one time the average patent flow of acquirors in the sample. Comparing the magnitudes of the effects on start-ups and acquirors, the increase in patenting performance of acquirors more than compensates for the reduction experienced by start-ups (as incumbents patent more on average as shown in Table 3.3. Further research would be needed to further investigate additional heterogeneities in the aggregate patterns.

However, the increase in patenting of acquirors reported in the second panel hides strong and important heterogeneities. Consistent with Stiebale (2016[48]), the effect on the acquiror is mainly driven by acquisitions that happen across industries and countries, that is, when firms are less likely to share a market. In fact, when restricting to acquisitions within industries and countries, there is a decrease in patenting activity on the side of the acquiror as well, as shown in the last panel. As explained above, killer acquisitions are most likely to happen if firms share a market which, in turn, is more likely to happen within industries and countries. This evidence provides further support for the evidence that anti-competitive reasons might drive the observed reduction in patenting.

Restricted Use - À usage restreint

Policy discussion

The findings in this paper indicate that the patenting activity of acquired start-ups decline sharply after acquisition. In fact, most acquisition targets stop patenting altogether in the years following the acquisition. Moreover, the acquiror does not exhibit a change in its patenting activity nor its quality following the acquisition.

The evidence provided in this paper mounts to the already existing evidence on the negative consequences on patenting activity, productivity, or the idea implementation of acquisition targets (Stiebale and Reize, 2011[47]; Bena and Li, 2014[15]; Stiebale, 2016[48]; Cunningham, Ederer and Ma, 2021[21]; Farre-Mensa, Liu and Nickerson, 2022[49]; Fons-Rosen, Roldán-Blanco and Schmitz, 2022[22]; Altomonte, El-Mallakh and Sonno, 2024[33]; Gregori, Martinez-Cirello and Nardo, 2023[66]). However, the channels through which this decline operates are much less understood, and, therefore, policy conclusions from this decline alone are hard to draw. Many explanations can be found to explain the patterns in the existing studies. A patenting decline can arise as the consequence of a change in IP strategies or the centralisation of the innovation activity in the acquiror company. This paper goes a step further and provides suggestive evidence on these mechanisms.

The analysis of the channels through which the decline in patenting activity operates suggests that incumbent companies engage in acquisitions with anti-competitive motives and not to take advantage of the start-ups technology to improve their own or increase their efficiency as measured through TFP. However, the implications for antitrust policy of these findings are nuanced. On the one hand, this paper underscores the importance of the long-run consequences on market structure when analysing the fusion of companies. Start-ups might not trigger antitrust authorities to intervene given their relatively small market shares, and, consequently, small effect on prices and concentration. However, market share measures of concentration might underestimate the negative consequences of the declining innovation on long-run market structure and business dynamism when analysing such acquisition cases. On the other hand, the prospect of being acquired might incentive start-up entry and innovation, an aspect that is missing in the current analysis and that could be an important channel to assess the aggregate consequences of these acquisitions.

Likewise, the average results reported in this paper hide many complex layers of heterogeneity. For instance, the paper shows that acquirors that engage in cross-border acquisitions in the EU do have a positive impact on their patenting performance, and this impact more than off-sets the negative impact on the targets. While this result suggests that there are some silver linings in the overall stark context portrayed in this paper, their implications must be assessed by policymakers with caution. Policymakers in the EU might be concerned about the centralisation of the innovative activity in the country of the incumbent company, which might cause innovation to shift location and increase cross-country or even regional inequalities within and across EU states.

Aside from the implications of the results for antitrust policy, this paper also contributes to a lively debate on how to scale up start-ups. On the one hand, a lot is yet to be understood of the consequences of different exit strategies on firm performance. For instance, comparative studies on the implications for innovation and other firm performance indicators of IPOs, remaining independent, or getting acquired are non-existent. This is a particularly relevant point given the recent trends that suggest start-ups are increasingly resorting to the latter as an exit strategy (Ederer and Pellegrino, 2023[27]). On the other hand, it is important to understand the structural factors that lead companies to choose one or another strategy. For instance, how does the depth of financial markets affect the choice of exit strategy? Are firms in markets where it is harder to raise funds more likely to succumb to incumbent acquirors? What kind of firms select into each exit strategy and how do these choices relate to macroeconomic conditions? All these questions remain largely unanswered in the literature and raise relevant concerns for policymakers that want to incentivise a resilient start-up and innovation ecosystem.

Restricted Use - À usage restreint

6 Conclusions

This paper sheds light on start-up acquisitions that have gained increasing relevance in recent years (see Figure 1.1). It provides a profile of start-ups and incumbents engaging in these interactions and assesses the impact on innovation performance. The paper builds on a unique and comprehensive cross-country dataset that combines information on start-ups, incumbents' stakes in these companies, and patenting activity as a measure of innovation. The broad and global coverage of the sample represents a key contribution of the study. By focusing on innovation and growth-oriented young firms, the study offers valuable new perspectives on start-ups and their interactions with incumbents, which is particularly important in the context of declining dynamism and rising market power.

The analysis provides strong evidence of the innovation motives behind these interactions. Start-ups that engage with incumbents generally exhibit stronger innovation performance before a deal, suggesting that incumbents' acquisitions might be driven by opportunities to access innovative technologies. The ex-ante characteristics of acquirors further support this view since the analysis shows that acquirors are more innovation-oriented with respect to other incumbents. Further, analysis of acquiror-target pairs indicates that technological proximity between the firms increases the likelihood of an acquisition.

While these results point to innovation motives behind the interactions between incumbents and start-ups, the findings could be rationalised in different ways. For example, the evidence that incumbents with higher innovation outcomes are more likely to engage in acquisitions could mean that acquirors need some level of absorptive capacity to effectively benefit from the interactions with start-ups. Alternatively, it may indicate that innovation leaders are more likely to engage in start-up acquisitions, potentially intending to suppress the most disruptive and innovative ones.

Next, the paper finds that acquisitions decrease start-ups' innovation performance. This decrease in innovation activity is not compensated by follow-on acquiror patenting activity. Several non-mutually exclusive explanations lend themselves to rationalising the negative innovation effect of incumbent interactions with start-ups. First, the decline in patenting activity might not reflect a decline in innovation. On the one hand, a decline in patenting activity might indicate a change in the IP strategies of the firm, opting for more privacy around the innovation process. On the other hand, it might reflect a shift from the development to the commercialisation of technologies. Second, several channels can account for a real decline in innovation, not just patenting. The innovation-for-buyout hypothesis posits that start-ups might seek to be acquired and reduce their incentives to invent after cashing out the monetary compensation. Alternatively, the killer acquisitions hypothesis suggests that acquisitions on behalf of acquirors might seek to suppress the start-ups' innovation to avoid the depreciation of its own technology and worthy competitors in the long run. Regarding these channels, this paper *provides suggestive* evidence that the results cannot be explained by a change in IP strategies or the shift to the commercialisation phase, suggesting that a true decline in innovation takes place. Likewise, it does not find evidence of start-ups innovating for buyouts, but it does find evidence supporting the killer acquisitions hypothesis.

The paper currently does not provide conclusive causal evidence on the mechanisms driving the acquisition results. Further investigating the mechanisms behind these findings might be part of future work by exploiting complementary data (e.g., inventors) or leveraging exogenous policy shocks that alter the trade-off between being acquired or staying independent.

Restricted Use - À usage restreint

References

Abadie, A. (2005), "Semiparametric difference-in-differences estimators", *Review of Economic Studies*, Vol. 72/1, pp. 1-19, https://doi.org/10.1093/ectj/utac017. [58]

Ackerberg, D., K. Caves and F. Garth (2015), "Identification Properties of Recent Production Function Estimators", *Econometrica*, https://doi.org/10.3982/ECTA13408. [74]

Akcgit, U. and W. Kerr (2018), "Growth through Heterogeneous Innovations", *The Journal of Political Economy*, Vol. 126/4, pp. 1374-1443, https://doi.org/10.1086/697901. [6]

Alexandridis, G., N. Antypas and N. Travlos (2017), "Value Creation from M&As: New Evidence", *Journal of Corporate Finance*, Vol. 45, pp. 632-650, https://doi.org/10.1016/j.jcorpfin.2017.05.010. [8]

Altomonte, C., N. El-Mallakh and T. Sonno (2024), "Business Groups, Strategic Acquisitions and Innovation", *CEP discussion paper CEPDP1996*, https://cep.lse.ac.uk/_NEW/publications/abstract.asp?index=10860. [33]

Arora, A., S. Belenzon and A. Patacconi (2017), "The decline of science in corporate R&D", *Strategic Management Journal*, Vol. 39/1, pp. 3-32, https://doi.org/10.1002/smj.2693. [10]

Arora, A., S. Belenzon and L. Sheer (2021), "Knowledge Spillovers and Corporate Investment in Scientific Research", *American Economic Review*, Vol. 111/3, pp. 871-898, https://doi.org/10.1257/aer.20171742. [11]

Atalay, E., A. Hortacsu and C. Syverson (2014), "Vertical Integration and Input Flows", *American Economic Review*, Vol. 104/4, pp. 1120-1148, https://doi.org/10.1257/aer.104.4.1120. [7]

Bajgar, M. et al. (2023), "Industry Concentration in Europe and North America", *Industrial and Corporate Change*, pp. 1-18, https://doi.org/10.1093/icc/dtac059. [17]

Barrot, J. (2016), "Investor Horizon and the Life Cycle of Innovative Firms: Evidence from Venture Capital", *Management Science*, Vol. 63/9, pp. 3021-3043, https://doi.org/10.1287/mnsc.2016.2482. [73]

Basberg, B. (1987), "Patents and the Measurement of Technological Change: A Survey of the Literature", *Research Policy*, Vol. 16/2-4, pp. 131-141, https://doi.org/10.1016/0048-7333(87)90027-8. [50]

Bellavitis, C., C. Fisch and S. Vismara (2023), "Monetary Policy and Venture Capital Markets", [9]

Restricted Use - À usage restreint

Review of Corporate Finance, Vol. 3/4, pp. 627-662, https://doi.org/10.1561/114.00000053.

Bena, J. and K. Li (2014), "Corporate Innovations and Mergers and Acquisitions", *The Journal of Finance*, Vol. 69/5, pp. 1923-1960, https://doi.org/10.1111/jofi.12059. [15]

Bloom, N. et al. (2020), "Are Ideas Getting Harder to Find?", *American Economic Review*, Vol. 110/4, pp. 1104-1144, https://doi.org/10.1257/aer.20180338. [12]

Bloom, N., M. Schankerman and J. Van Reenen (2013), "Identifying Technology Spillovers and Product Market Rivalry", *Econometrica*, Vol. 81/4, pp. 1347-1393, https://doi.org/10.3982/ECTA9466. [13]

Borusyak, K., X. Jaravel and J. Spiess (2024), "Revisiting Event-Study Designs: Robust and Efficient Estimation", *Review of Economic Studies*, p. rdae007, https://doi.org/10.1093/restud/rdae007. [59]

Breschi, S., J. Lassébie and C. Menon (2018), *A Portrait of Innovative Start-ups across Countries*, https://doi.org/10.1787/f9ff02f4-en. [34]

Cabral, L. (2018), "Standing on the Shoulders of Dwarfs", *CEPR Discussion Paper No. DP13115*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3235598. [37]

Callaway, B. and P. Sant'Anna (2021), "Difference-in-Differences with multiple time periods", *Journal of Econometrics*, Vol. 225, pp. 200-230, https://doi.org/10.1016/j.jeconom.2020.12.001. [60]

Calligaris, S. et al. (2024), *Exploring the Evolution and the State of Competition in the EU*. [18]

Calligaris, S. et al. (2024b), "Industry concentration in Europe: trends and methodological insights", *OECD Science, Technology and Industry Working Papers*. [57]

Calvino, F. et al. (2018), "A taxonomy of digital intensive sectors"*, OECD Science, Technology and Industry Working Papers*, No. 2018/14, OECD Publishing, Paris, https://doi.org/10.1787/f404736a-en. [56]

Calvino, F., C. Criscuolo and R. Verlhac (2020), "Declining business dynamism: Structural and policy determinants"*, OECD Science, Technology and Industry Policy Papers*, No. 94, OECD Publishing, Paris, https://doi.org/10.1787/77b92072-en. [19]

Cavenaile, L., M. Celik and X. Tian (2021), "The Dynamic Effects of Antitrust Policy on Growth and Welfare", *Journal of Monetary Economics*, Vol. 121, pp. 42-59, https://doi.org/10.1016/j.jmoneco.2021.04.011. [29]

Cunningham, C., F. Ederer and S. Ma (2021), "Killer Acquisitions", *Journal of Political Economy*, Vol. 129/3, pp. 649-702, https://doi.org/10.1086/712506. [21]

Dahlin, K. and D. Behrens (2005), "When is an invention really radical?: Defining and measuring technological radicalness", *Research Policy*, Vol. 34/5, pp. 717-737, https://doi.org/10.1016/j.respol.2005.03.009. [75]

de Chaisemartin, C. and X. D'Haultfoeuille (2024), "Difference-in-Differences Estimators of Intertemporal Treatment Effects", *Review of Economics and Statistics*, pp. 1-45, https://doi.org/10.1162/rest_a_01414. [63]

de Chaisemartin, C. and X. D'Haultfoeuille (2023), "Two-way fixed effects and differences-in- [68]

Restricted Use - À usage restreint

differences with heterogeneous treatment effects: a survey", *The Econometrics Journal*, Vol. 26/3, pp. C1-C30, https://doi.org/10.1093/ectj/utac017.

de Chaisemartin, C. and X. d'Haultfoeuille (2021a), "Two-way fixed effects regressions with several treatments", *arXiv preprint arXiv:2012.10077.*. [62]

De Ridder, M. (2024), "MArket Power and Innovation in the Intangible Economy", *American Economic Review*, Vol. 114/1, pp. 199-251, https://doi.org/10.1257/aer.20201079. [55]

Denicolo, V. and M. Polo (2021), *Acquisitions, Innovation and the Entrenchment of Monopoly*, https://doi.org/10.2139/ssrn.3988255. [42]

Dickinson, V. (2011), "Cash Flows Patterns as a Proxy for Firm Life Cycle", *The Accounting Review*, Vol. 86/6, pp. 1969-1994, https://doi.org/10.2308/accr-10130. [53]

Didier, T. et al. (2021), "Capital Market Financing and Firm Growth", *Journal of Inernational Money and Finance*, Vol. 118, pp. 1024-1059, https://doi.org/10.1016/j.jimonfin.2021.102459. [16]

Ederer, F. and B. Pellegrino (2023), "The Great Start-up Sellout and the Rise of Oligopoly", *AEA Papers and Proceedings*, Vol. 113, pp. 274-278, https://doi.org/10.1257/pandp.20231024. [27]

European Commission (2024), *The Future of European Competitiveness*. [54]

European Commission (2024), *The Future of European Competitiveness*. [24]

Ewens, M. and J. Farre-Mensa (2020), "The Deregulation of the Private Equity Markets and the Decline in IPOs", *The Review of Financial Studies*, Vol. 33/12, pp. 5463-5509, https://doi.org/10.1093/rfs/hhaa053. [26]

Farre-Mensa, J., Z. Liu and J. Nickerson (2022), *Do Start-up Patent Acquisitions Affect Inventor Productivity?*, https://doi.org/10.2139/ssrn.4071917. [49]

Federico, G., G. Langus and T. Valletti (2017), "A Simple Model of Mergers and Innovation", *Economic Letters*, Vol. 157/C, pp. 136-140, https://doi.org/10.1016/j.econlet.2017.06.014. [41]

Fons-Rosen, C., P. Roldán-Blanco and T. Schmitz (2022), *The Effects of Startup Acquisitions on Innovation and Economic Growth*, https://doi.org/10.2139/ssrn.3785485. [22]

Fumagalli, C., M. Motta and E. Tarantino (2020), *Shelving or Developing? The Acquisition of Potential Competitors Under Financial Constraints*. [39]

Gans, J., H. H. and S. Stern (2002), "When Does Start-up Innovation Spur the Gale of Creative Destruction?", *RAND Journal of Economics*, Vol. 33/4, pp. 571-586, https://doi.org/10.2307/3087475. [5]

García-Santana, M. et al. (2024), *Firms' Participation in Capital Markets and Real Economic Outcomes*. [40]

Gautier, A. and J. Lamesch (2021), "Mergers in the Digital Economy", *Information Economics and Policy*, Vol. 54, https://doi.org/10.1016/j.infoecopol.2020.100890. [44]

Giot, P. and A. Schwienbacher (2007), "IPOs, trade sales and liquidations: Modelling venture capital exits using survival analysis", *Journal of Banking and Finance*, Vol. 31/3, pp. 679- [25]

Restricted Use - À usage restreint

702, https://doi.org/j.jbankfin.2006.06.010.

Goodman-Bacon, A. (2021), "Difference-in-differences with variation in treatment timing", *The Journal of Econometrics*, Vol. 225/2, pp. 254-277, https://doi.org/10.1016/j.jeconom.2021.03.014. [69]

Gregori, W., M. Martinez-Cirello and M. Nardo (2023), "The Effects of Cross-Border Acquisitions on Firms' Productivity in the EU", *The World Economy*, Vol. 47/1, pp. 9-36, https://doi.org/10.1111/twec.13521. [66]

Guadalupe, M., O. Kuzmina and C. Thomas (2012), "Innovation and Foreign Ownership", *American Economic Review*, Vol. 102/7, pp. 3594-3627, https://doi.org/10.1257/aer.102.7.3594. [67]

Haltiwanger, J., R. Jarmin and J. Miranda (2013), "Who Creates Jobs? Small Versus Large Versus Young", *The Review of Economics and Statistics*, Vol. 95/2, pp. 347-361, https://doi.org/10.1162/REST_a_00288. [1]

Haucap, J., A. Rasch and J. Stiebale (2019), "How Mergers Affect Innovation: Theory and Evidence", *International Journal of Industrial Organization*, Vol. 63, pp. 283-325, https://doi.org/10.1016/j.ijindorg.2018.10.003. [43]

Hoberg, G. and G. Phillips (2010), "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis", *Review of Financial Studies*, Vol. 23, pp. 3773-3811, https://doi.org/10.1093/rfs/hhq053. [32]

Hsu, P. et al. (2021), "2021", *Journal of International Money and Finance*, Vol. 112, https://doi.org/10.1016/j.jimonfin.2020.102320. [36]

Jaffe, A. (1986), "Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value", *American Economic Review*, Vol. 76/5, pp. 984-1001. [52]

John Haltiwanger, E. (ed.) (2017), *High-Growth Young Firms: Contribution to Job, Output, and Productivity Growth*, University of Chicago Press. [2]

Kortum, S. and J. Lerner (2000), "Assessing the Contribution of Venture Capital to Innovation", *RAND Journal of Economics*, Vol. 31/4, pp. 674-692, https://doi.org/10.2307/2696354. [3]

Letina, I., A. Schmutzler and R. Seibel (2021), *Killer Acquisitions and Beyond: Policy Effects on Innovation Strategies*, https://doi.org/10.2139/ssrn.367150. [38]

Li, X., T. Liu and L. Taylor (2023), "Common Ownership and Innovation Efficiency", *Journal of Financial Economics*, Vol. 147/3, pp. 475-497, https://doi.org/10.1016/j.jfineco.2022.12.004. [72]

Ma, S. (2019), "The Life Cycle of Corporate Venture Capital", *The Review of Financial Studies*, Vol. 33/1, pp. 358-394, https://doi.org/10.1093/rfs/hhz042. [71]

Olsen, A. and J. Moen (2022), "The triple difference estimator", *The Econometrics Journal*, Vol. 25/3, pp. 531-553, https://doi.org/10.1093/ectj/utac010. [64]

Park, M., E. Leahey and R. Funk (2023), "Papers and Patents Are Becoming Less Disruptive Over Time", *Nature*, Vol. 613, pp. 138-144, https://doi.org/10.1038/s41586-022-05543-x. [20]

Phillips, G. and A. Zhdanov (2013), "R&D and the Inventives from Merger and Acquisition [31]

Restricted Use - À usage restreint

Activity", *The Review of Financial Studies*, Vol. 26/1, pp. 34-78, https://doi.org/10.1093/rfs/hhs109.

Rhodes-Kropf, M. and D. Robinson (2008), "The Market for Mergers and the Boundaries of the Firm", *The Journal of Finance*, Vol. 63/3, pp. 1169-1211, https://doi.org/10.1111/j.1540-6261.2008.01355.x. [14]

Schnitzer, M. and M. Watzinger (2022), "Measuring the Spillovers of Venture Capital", *The Review of Economics and Statistics*, Vol. 104/2, pp. 276-292, https://doi.org/10.1162/rest_a_00937. [4]

Seru, A. (2014), "Firm Boundaries Matter: Evidencefrom Conglomerates and R&D Activity", *Journal of Financial Economics*, Vol. 111/2, pp. 381-405, https://doi.org/10.1016/j.jfineco.2013.11.001. [46]

Sevilir, M. and X. Tian (2010), *Acquiring Innovation*, https://doi.org/10.2139/ssrn.1731722. [45]

Squicciarini, M., H. Dernis and C. Criuscolo (2013), "Measuring Patent Quality: Indicators of Technological and Economic Value", *OECD Science, Technology, and Industry Working Papers 2013/03*, https://doi.org/10.1087/5k4522wkw1r8-en. [51]

Stiebale, J. (2016), "Cross-Border M&As and Innovative Activity of Acquiring and Target Firms", *Journal of International Economics*, Vol. 99, pp. 1-15, https://doi.org/10.1016/j.jinteco.2015.12.005. [48]

Stiebale, J. and F. Reize (2011), "The Impact of FDI through Mergers and Acquisitions on Innovation in Target Firms", *International Journal of Industrial Organization*, Vol. 29, pp. 155-167, https://doi.org/10.1016/j.ijindorg.2010.06.003. [47]

Sun, L. and S. Abraham (2021), "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects", *Journal of Econometrics*, Vol. 225, pp. 175-199, https://doi.org/10.1016/j.jeconom.2020.09.006. [61]

Veugelers, R. and C. Schneider (2018), "Which IP Strategies Do Young Highly Innovative Firms Choose?", *Small Business Economics*, Vol. 50, pp. 113-129, https://doi.org/10.1007/s11187-017-9898-y. [65]

Wang, X. (2018), *Catering Innovation: Entrepreneurship and the Acquisition Market*, https://doi.org/10.2139/ssrn.3247274. [35]

Warg, K. (2022), *The Acquisition Option and Start-up Innovations*. [23]

Weiss, J. (2023), *Market Concentration, Growth and Acquisitions*. [30]

Wolfers, J. (2006), "Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results", *American Economic Review*, Vol. 96/5, pp. 1802-1820, https://doi.org/10.1257/aer.96.5.1802. [70]

Zhao, X. (2009), "Technological Innovation and Acquisitions", *Management Science*, Vol. 55/7, pp. 1170-1783, https://doi.org/10.1287/mnsc.1090.1018. [28]

Restricted Use - À usage restreint

Annex A. Supplementary material

Table A A.1. Descriptive statistics of the acquisition sample

		Start-ups	Incumbents
Firms		91 914	156 681
	Treatment	17 854	11 120
	Control	74 060	145 561
3-digit sectors		204	217
Top 5 sectors			
		Information services (28%)	Financial services (31%)
		Scientific R&D (9%)	Auxiliary services to financials (15%)
		Publishing (9%)	Information services (6%)
		Computer services, consultancy, and programming (8%)	Computer services, consultancy, and programming (5%)
		Manufacture of computer, electronic and optical products (5%)	Activities of head offices (3%)
Countries		60	74
Top 5 countries			
		US (44%)	US (28%)
		EU (17%)	EU (22%)
		UK (8%)	China (11%)
		China (8%)	UK (9%)
		India (4%)	Japan (5%)

Note: Number of firms and their composition across industries and countries in the acquisition sample.
Source: OECD calculations using Orbis M&A and the OECD/STI Start-ups Database.

Restricted Use - À usage restreint

Annex B. Robustness

A description of VC-funded acquired start-ups

1. Because of the sample selection, start-ups that have a patent might be driving the results of the ex-ante analysis if VC firms are not usually holders of patents. While this per se does not go against the idea that acquisitions are concentrated in innovative companies, it complicates the interpretation of the intensive and extensive margins of innovation. For this reason, Table A B.1 shows the description of the acquired start-ups restricting to those that have VC, i.e., shutting down one of the sample selection criteria. As can be observed, the magnitudes remain substantially different across the extensive and intensive margins, suggesting that the first-time patenting event is indeed more influential than the subsequent ones even when leaving firms selected on patents out of the sample. Albeit there is a decrease in magnitude in the first column, the within-firm specification remains remarkably similar.

Table A B.1. A description of VC-funded acquired start-ups – which characteristics make start-ups more likely to be acquired?

	Cross-section			Within-firm		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Has a patent	0.00103*			0.00723***		
	(0.000606)			(0.000944)		
Patent stock		0.0266**			0.0500***	
		(0.0108)			(0.0136)	
Citations-weighted patent stock			0.0165***			0.0150***
			(0.00405)			(0.00574)
VC stock	0.000482***	0.00121***	0.00119***	0.00121***	0.00115***	0.00114***
	(3.43e-05)	(6.06e-05)	(6.08e-05)	(3.77e-05)	(6.02e-05)	(6.03e-05)
Only patenting start-ups	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	515 471	157 370	157 370	643 334	201 548	201 548
R-squared	0.054	0.064	0.064	0.146	0.144	0.144
Mean dep. variable	2.2	2.0	2.0	1.8	1.6	1.6
Premium	4.6	0.8	2.2	40.0	1.8	2.5

Note: This table restricts observations to those that have a VC-funding event before the age of 10. The table shows the results of the linear probability model (Equation 1) using cross-sectional variation for different specifications. The first column allows the effect of having a patent to vary across age categories. The second and third columns only include acquisitions that happen across and within 3-digit NACE Rev. 2 industries, respectively. The fourth and fifth columns only include acquisitions that happen across or within countries, respectively. The control group never changes. The mean dependent variable reports the unconditional probability of being acquired in the relevant sample as a percentage. The premium represents the ratio between the coefficient of having a patent and the mean dependent variable as a percentage. All regressions control for the firm's age and industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on OECD/STI Start-ups Database, Orbis M&A, and PATSTAT data.

Restricted Use - À usage restreint

Heterogeneity across acquirors in ex-ante characteristics

Table 6.1. Heterogeneity across acquirors.

	Industries		Countries	
	Across	Within	Across	Within
	(1)	(2)	(3)	(4)
Has a patent$_{t-1}$	0.0103***	0.0055***	0.0050***	0.0107***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Industry-Country-Year FE	Yes	Yes	Yes	Yes
Observations	2 987 542	2 983 380	2 982 498	2 988 424
R-squared	0.038	0.046	0.048	0.040
Mean dep. variable	0.3	0.2	0.1	0.3
Premium	334.6	320.3	354.2	317.8

Note: The table shows the results of the linear probability model using cross-sectional variation for different specifications exploring heterogeneity across acquirors. The first and second columns only include acquisitions that happen across and within 3-digit NACE Rev. 2 industries, respectively. The third and fourth columns only include acquisitions that happen across or within countries, respectively. The average dependent variable reports the unconditional probability of being acquired in the relevant sample. The premium shows the coefficient of interest as a percentage of the mean dependent variable. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on OECD/STI Start-ups Database, Orbis M&A, and PATSTAT.

Estimating the effect of acquisitions on innovation using propensity score matching

2. In this section, an alternative to using not-yet-treated as a control group is presented. The methodology used in this section combines the de Chaisemartin and D'Haultfoeuille (2024[63]) estimation strategy with the traditional propensity score matching as in Guadalupe, Kuzmina, and Thomas (2012[67]). In particular, this methodology computes the propensity score to be treated of each firm by running a logit specification where the dependent variable is a dummy that takes value 1 if an acquisition takes place and 0 otherwise. The independent variables are again the age of the start-up and its VC stock level. The results of the propensity score estimation and the balance check across acquired start-ups and start-ups in the control group are reported in Table 6.2 and Table 6.2. Propensity score estimation and balance test

Panel A. Propensity score estimation		
Age	0.0266***	
	(0.0005)	
VC stock	0.0137***	
	(0.0005)	
Observations	954 023	
Pseudo R-squared	0.02	
Panel B. Balance test: Patent flows		
Treated	Control	Difference (t-statistic)
0.0004	0.0005	-0.0001 (-1.6)

Note: Panel A in this table shows the results of the logit estimation of the probability of acquisition on age and VC stock level. Panel B shows the average standardised patent flows across treated and untreated observations as well as their difference. t-statistic in parenthesis.
Source: OECD calculations based on OECD/Start-ups Database, Orbis M&A, and PATSTAT.

Restricted Use - À usage restreint

3. The results of DID estimation using the propensity score matching technique is shown in Figure 6.2. As can be observed, the results remain qualitatively similar when using this technique to analyse the post-acquisition performance of start-ups. While the patent flow decreases substantially after the acquisition, the citations remain constant until declining due to the absence of new patents and the obsolescence of old ones. The magnitude of the coefficient, nevertheless, increases substantially. While the DID in **Error! Reference source not found.** showed that the patent flow decreases by one time its average value before the acquisition, here the reduction is almost twice as large. As for citations, the results mimic those of the baseline specification in Section 5.

4. Figure 6.1.[56] As observed, the matching procedure produces comparable groups for the estimation with similar levels of patenting activity, age, and VC stocks. These propensities scores are used as weights in the de Chaisemartin and D'Haultfoeuille (2024[63]) estimation. Treated companies are weighted according to *1/PS* and never-treated companies are weighted by *PS/(1-PS),* where *PS* is each firm's propensity score.

Table 6.2. Propensity score estimation and balance test

Panel A. Propensity score estimation		
Age	0.0266***	
	(0.0005)	
VC stock	0.0137***	
	(0.0005)	
Observations	954 023	
Pseudo R-squared	0.02	
Panel B. Balance test: Patent flows		
Treated	Control	Difference (t-statistic)
0.0004	0.0005	-0.0001 (-1.6)

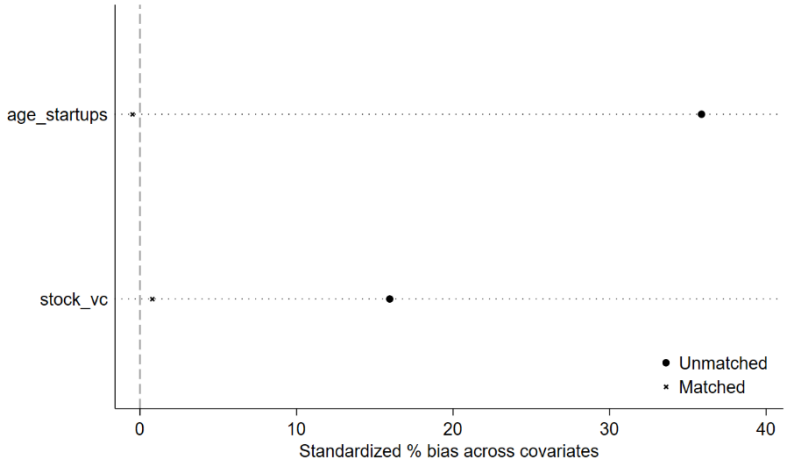
Note: Panel A in this table shows the results of the logit estimation of the probability of acquisition on age and VC stock level. Panel B shows the average standardised patent flows across treated and untreated observations as well as their difference. t-statistic in parenthesis.
Source: OECD calculations based on OECD/Start-ups Database, Orbis M&A, and PATSTAT.

5. The results of DID estimation using the propensity score matching technique is shown in Figure 6.2. As can be observed, the results remain qualitatively similar when using this technique to analyse the post-acquisition performance of start-ups. While the patent flow decreases substantially after the acquisition, the citations remain constant until declining due to the absence of new patents and the obsolescence of old ones. The magnitude of the coefficient, nevertheless, increases substantially. While the DID in **Error! Reference source not found.** showed that the patent flow decreases by one time its average value before the acquisition, here the reduction is almost twice as large. As for citations, the results mimic those of the baseline specification in Section 5.

[56] The command **psmatch2** in STATA is implemented to compute the propensity score matching.

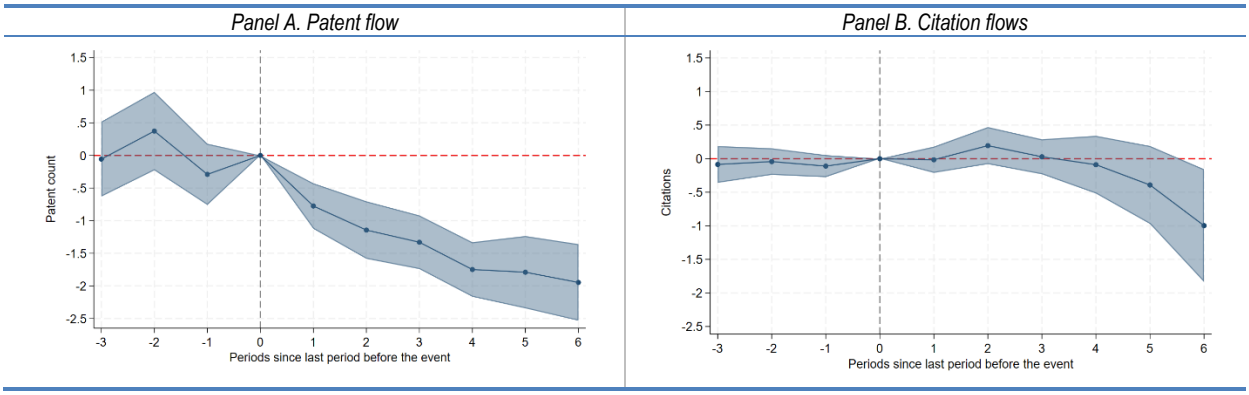
Restricted Use - À usage restreint

Figure 6.1. Bias reduction in observable characteristics across treatment and control start-ups



Note: This figure shows the reduction in the differences across the age of start-ups and their VC levels when weighting observations by their propensity scores. The round point indicates the difference in averages in percentages in the start-ups age and VC stock across treatment and control groups when firms are not weighted by their propensity scores. The crosses indicate the difference in averages in percentages in the start-ups age and VC stock across treatment and control groups when firms are weighted by their propensity scores.
Source: OECD calculations using data from the OECD/Start-ups Database, ORBIS M&A, and PATSTAT.

Figure 6.2. The effect of acquisitions on patenting activity using propensity score matching



Notes: Figure 6.2 shows the difference in the number of applied inventions in Panel A of acquired companies vis-à-vis not-yet-treated start-ups using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[63]). All panels use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A

Restricted Use - À usage restreint

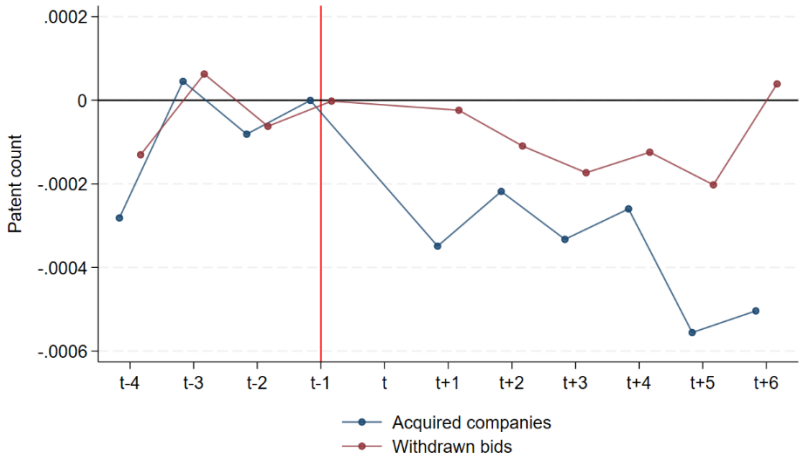
Estimating the effect of acquisitions on innovation using an exogenous shock

Table 6.3. Balance check across exogenously withdrawn and successful bids

VARIABLES	(1)
log(1+Patent flow)	0.0126
	(0.1706)
log(1+Citations)	0.7737
	(9.5656)
Industry-Country-Year FE	Yes
Observations	7 016
R-squared	0.197

Note: The table shows the results of Equation 1 using cross-firm variation. The specification shows the effect of the patent flow and the patent citations on the probability of acquisition as in the ex-ante exercises. The treatment group is restricted only to the year of acquisition and the control group only to those start-ups that received exogenously withdrawn bids on the year of the withdrawal. All regressions control for the firm's age, VC stock levels, and industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A.

Figure 6.3. Event study of the patent flow across acquired start-ups and start-ups with exogenously withdrawn bids



Note: This figure shows the average standardised patent flows across acquired start-ups and those start-ups with exogenously withdrawn bids after th acquisition event or the acquisition withdrawal.
Source: OECD calculations based on OECD/Start-ups Database, Orbis M&A, and PATSTAT.

Restricted Use - À usage restreint